Title
Self-redundant Real-time Fault Diagnosis of Battery Systems in Electrified Vehicles

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Self-redundant Real-time Fault Diagnosis of Battery Systems in Electrified Vehicles

A dissertation submitted in partial satisfaction of the requirements for the degree Doctor of Philosophy in Engineering Science (Electrical and Computer Engineering) by Bing Xia

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2017
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Co-Chair

Co-Chair

University of California, San Diego

2017
DEDICATION

To those love me and I love.
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LIST OF ABBREVIATIONS

ADC  Analog to Digital Converter
BMS  Battery Management System
CT   Continuous-time
DT   Discrete-time
ECM  Equivalent Circuit Model
ESC  External Short Circuit
EV   Electric Vehicle
HEV  Hybrid Electric Vehicle
HPPC Hybrid Pulse Power Characterization
ICE  Internal Combustion Engine
ISC  Internal Short Circuit
LS   Least Squares
IV   Instrumental Variable
OCV  Open Circuit Voltage
PHEV Plug-in Hybrid Electric Vehicle
SoC  State of Charge
SoH  State of Health
SoP  State of Power
SNR  Signal to Noise Ratio
SVF  State Variable Filter
UDDS Urban Dynamometer Driving Schedule
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In this dissertation, Chapter 2 is based on the following published papers. As the first authors, I conducted the experiments, did the data analysis, extended the application of the theory to Lithium-ion batteries and drafted the paper.


B. Xia, C. Mi, Z. Chen, B. Robert, “Multiple cell lithium ion battery system electric fault online diagnostics”, IEEE Transportation Electrification Conference and Expo, 2015.

Chapter 3 is based on the following published paper. As the first author, I conducted the experiments, did the data analysis, extended the application of the theory to Lithium-ion batteries and drafted the paper.

B. Xia, X. Zhao, R. de Callafon, H. Garnier, T. Nguyen, C. Mi, “Accurate lithium ion
battery parameter estimation with continuous-time system identification methods”, 

Chapter 4 is based on the following published paper. As the first author, I conducted the experiments, did the data analysis, developed the theory and drafted the paper.


Chapter 5 is based on the following published papers. As the first authors, I conducted the experiments, did the data analysis, developed the theory and drafted the paper.


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Journal Publications


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B. Xia, C. Mi, Z. Chen, B. Robert, “Multiple cell lithium ion battery system electric fault online diagnostics”, *IEEE Transportation Electrification Conference and Expo (ITEC)*, 2015.


ABSTRACT OF THE DISSERTATION

Self-redundant Real-time Fault Diagnosis of Battery Systems in Electrified Vehicles

by

Bing Xia

Doctor of Philosophy in Engineering Science (Electrical and Computer Engineering)

University of California San Diego, 2017
San Diego State University, 2017

Professor Chris Mi, Co-Chair
Professor Truong Nguyen, Co-Chair

As electrified vehicles penetrate the market, consumers have been gradually experiencing the benefits of their high performance and contribution towards green living. However, the benefits of the new powertrain system bring with them many severe safety hazards, which hinder their development. The early detection of electric faults is an essential approach to identifying the occurrence of hazards and ensuring safe operation. This thesis studies state-of-the-art fault diagnosis methods for the battery system in electrified vehicles. Based on the uniqueness of the battery system, the self-redundant fault detection methods are proposed and studied in detail.

First, abundant experiments are conducted to capture the electrical and thermal behaviors of the lithium ion battery cells, serving as the basic energy storage elements in the commercial battery packs nowadays, and the simple threshold-based fault detection method is implemented to identify electric faults, including over charge, over discharge, external short circuit and internal short circuit.

Then, the model-based fault detection method is investigated to compensate the drawback of the threshold-based diagnosis method, in which the input information is ignored. The continuous-time system identification methods are introduced to estimate model parameters of the equivalent circuit model. The estimated model
provides more accurate and robust fault detection performance compared with that of the traditional discrete-time system identification methods.

Next, the correlation-based fault diagnosis method is proposed for short circuit detections in the battery system. This method does not require the preliminary effort in battery modeling, identification and validation. More importantly, the correlation coefficient is not sensitive to variations in open circuit voltages and internal resistances, and thus is robust to cell inconsistencies in real applications.

After that, the theory of the interleaved voltage measurement method is developed to distinguish between sensor and cell failure without extra hardware components or battery models. The theory is then improved such that the constraint in sensor topology is removed by varying the sensor matrix. The feasibility of the measurement method is validated by simulation and experiment.

At last, the interleaved voltage measurement method is integrated with the correlation-based fault diagnosis method to achieve both the advantages. The viability of the integration is confirmed by experiment validation.

In summary, this thesis develops the self-redundant fault diagnosis approaches, including the correlation-based short circuit detection method and the interleaved voltage measurement method. These methods are specifically designed for the battery system, in which duplicative components and similar measurements are needed. The advantages of the proposed self-redundant fault diagnosis methods over the state-of-the-art redundancy-based methods are listed as follows,

i) The implementation of hardware redundancy is not necessary.

ii) No cell testing, modeling and validation work are required.

iii) The method is robust to cell inconsistencies in battery states.

iv) The ambiguity in cell and sensor failure is resolved upon fault occurrence.

The disadvantages of the proposed fault detection methods are

i) More computation power is needed to implement online.

ii) The noise level of the voltage measurements is increased.
Chapter 1

Introduction

1.1 Background

1.1.1 Electrified vehicles

On August 2012, the U.S. Environmental Protection Agency (EPA) and the National Highway Traffic Safety Administration (NHTSA) released standards to limit tailpipe pollution and increase fuel economy for passenger cars, light-duty trucks, and medium-duty passenger vehicles, for the model years 2017 through 2025 [1]. The standards were developed as part of the second phase of a national program aiming at reducing greenhouse gas emissions and protecting the earth from global warming.

The finalized regulation sets fleet-wide average carbon dioxide (CO$_2$) emission standards to the manufacturers, in which each compliance target is based on the CO$_2$ emission and the footprint (size) of a specific vehicle. Table 1.1 shows the projected compliance targets of the CO$_2$ emissions and the equivalent fuel economy in the regulation period. The table indicates that, by the end of 2025, the combined fuel economy of passenger cars and light trucks will have reached 54.5 mpg, which is 53% greater than the base condition in 2016. The automotive manufacturers have developed and applied a wide range of technologies to ensure compliance with the standards, including advancements in existing internal combustion engines (ICEs) [2], transmission systems [3], vehicle lightweighting [4], aerodynamics [5], auxiliary components [6], and most importantly, vehicle electrification [7].
Table 1.1: Projected fleet-wide emission compliance targets in CO₂ emissions and fuel economy.[1]

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Vehicle electrification involves adding electrical powering systems into the powertrain of conventional ICE vehicles [8, 9]. In general, an electrical powering system consists of a battery pack and an electric motor, which can be regarded as an electrical duality of the existing fuel tanks and ICEs in conventional vehicles. Apart from the fact that the energy conversion efficiency of motors is much higher than that of ICEs [10], the electrical-mechanical hybridization greatly diversifies powertrain architectures and provides various means to save energy. One straightforward approach is to distribute the vehicle power demand in an optimized way such that the sweet point of the ICE is mostly guaranteed [11]. A second common approach is to use an electric motor to regenerate the vehicle kinetic energy lost in mechanical braking into electrical energy and store it in an onboard battery pack [12, 13].

In addition to benefits realized in fuel saving, an electrical powering system offers superior dynamic performance to the traditional ICE powering system. The vehicle start-stop acceleration is boosted due to the fast electro-magnetic nature of motors and their large torque at low speeds [14]. The small size of motors also enables various powertrain configurations, including dual motor [15] and in-wheel motor [16] models. The powering and control flexibilities of these models are significantly enhanced, which cannot be easily achieved by a traditional ICE configuration.

Based on the different levels of electrical/mechanical powering hybridization, vehicles can be grouped into ICE vehicles, hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and electric vehicles (EVs) [17]. Typical powertrain architectures and the corresponding commercial vehicles are shown in Figure 1.1.
Electrified vehicles play an important role in addressing the energy crisis and greenhouse effects. A major component in electrified vehicles is the battery system, which stores the electrical energy in the electrochemical form.

The basic working principles of rechargeable (secondary) batteries are demonstrated in Figure 1.2. A rechargeable battery is mainly composed of an anode, cathode, electrolyte, and separator [18]. The anode and cathode are made from different metals or metallic compounds. When they are both immersed in the electrolyte, a potential difference is produced by the two different materials. If a separator is inserted in the electrolyte to prevent electron flow, and an external circuit loop is built, the electrons will flow through the external circuit to the cathode, while the cations left in the anode will flow internally through the separator to the cathode. Hence, the flow of electrons in the external circuit releases electrical energy, and the charge

**Figure 1.1:** Typical powertrain architectures and their corresponding commercial vehicles.

### 1.1.2 Lithium ion batteries

Electrified vehicles play an important role in addressing the energy crisis and greenhouse effects. A major component in electrified vehicles is the battery system, which stores the electrical energy in the electrochemical form.

The basic working principles of rechargeable (secondary) batteries are demonstrated in Figure 1.2. A rechargeable battery is mainly composed of an anode, cathode, electrolyte, and separator [18]. The anode and cathode are made from different metals or metallic compounds. When they are both immersed in the electrolyte, a potential difference is produced by the two different materials. If a separator is inserted in the electrolyte to prevent electron flow, and an external circuit loop is built, the electrons will flow through the external circuit to the cathode, while the cations left in the anode will flow internally through the separator to the cathode. Hence, the flow of electrons in the external circuit releases electrical energy, and the charge
balance is maintained by both the internal and external flow, as illustrated in Figure 1.2. In contrast, when a battery is charged, the electrons are pumped from the anode to the cathode through the external circuit, while the cations are forced to flow internally. In the process, the electrochemical potential of the anode and cathode is elevated, thus, external energy is stored in the battery.

Different materials demonstrate different electrochemical properties, which have a great impact on the energy and power performances of the assembled batteries [19]. There have been mainly three types of batteries applied in EV applications, namely, lead acid batteries, nickel metal hydride batteries and lithium ion batteries [20, 21]. A detailed comparison among the energy storage media in different types of electrified vehicles can be found in the Ragone plot [22], in which different energy storage solutions are compared based on specific power and specific energy. The comparison shows that lithium ion batteries have the advantages of high specific energy and high specific power. This performance can meet the general goal for PHEVs, but continuing effort is still needed to compete with ICE vehicles in the realm of specific energy. In addition to the properties demonstrated by the Ragone plot, lithium ion batteries also exhibit the merit in long life cycles and they are free of memory effect. Therefore, lithium ion batteries are the most widely used energy storage media in vehicle electrification [23].

**Figure 1.2:** Basic working principle of rechargeable batteries.
1.1.3 Battery management and safety of battery systems

The voltage and current level of an individual battery cell is constrained by its electrochemical material properties. However, a typical battery pack powering a passenger EV demands a typical voltage level of 400 V and a peak current level of 500 A. This requires abundant battery cells connecting in series and parallel to sustain sufficient power and energy levels. The need to manage a large number of battery cells gives rise to a key component of the battery system, i.e., the battery management system (BMS) [24].

The major task for a BMS is to ensure the safe and efficient operation of the battery pack. This objective is achieved by the collaboration of the key BMS functions, including battery cell monitoring, states estimation, charge control, cell balancing, thermal management, and safety and protection [25], as illustrated in Figure 1.3.

Typically, the voltage of each battery cell, the current for the whole pack, and several temperature spots within the battery pack are monitored when a BMS

![Figure 1.3: Key functions of BMSs in electrified vehicles.](image-url)
is activated. This information is then used to estimate the essential states of the battery pack, namely, the state of charge (SoC) [26], state of health (SoH) [27], state of power (SoP) [28], etc. Based on the estimates, the BMS determines the power level the battery pack can sustain to best meet the power demand. The cell balancing function is specifically designed to maintain the charge consistency among the battery cells in a pack [29]. Due to inherent manufacturing inconsistencies or variation in thermal conditions, battery cells exhibit different electrical performances as the cells age. These inconsistencies lower the capacity of a battery pack, and increase the threat of over charge and over discharge, which cause permanent damage [30]. Moreover, the rate of electrochemical reactions needs to be controlled within a rapid but safe rate. Therefore, a thermal management system is required to heat and cool the battery pack when necessary [31]. Last but not least, the safety and protection function diagnoses the faulty battery cells, isolates the fault locations and triggers the corresponding mitigation methods [32].

It is important to note that the safety and protection function is the most crucial function among all the features of a BMS. A non-qualified protection function may lead to severe property damages and threaten end users’ lives. Table 1.2 lists some of the fire accidents worldwide related to electrified vehicles from 2010 through 2016.

**Table 1.2:** List of fire accidents related to electrified vehicles.

<table>
<thead>
<tr>
<th>No.</th>
<th>Date</th>
<th>Location</th>
<th>Involved vehicles</th>
<th>Causes</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2010.01</td>
<td>Urumqi, China</td>
<td>EV bus</td>
<td>Cell overheating</td>
</tr>
<tr>
<td>2</td>
<td>2011.04</td>
<td>Hangzhou, China</td>
<td>Zhongtai EV taxi</td>
<td>Cell internal damage</td>
</tr>
<tr>
<td>3</td>
<td>2012.05</td>
<td>Shenzhen, China</td>
<td>BYD EV taxi</td>
<td>Vehicle rear crash</td>
</tr>
<tr>
<td>4</td>
<td>2013.01</td>
<td>Kagawa, Japan</td>
<td>Boeing 787 battery</td>
<td>Cell internal damage</td>
</tr>
<tr>
<td>5</td>
<td>2014.07</td>
<td>Beijing, China</td>
<td>Tesla Model S</td>
<td>Vehicle crash to pole</td>
</tr>
<tr>
<td>6</td>
<td>2015.04</td>
<td>Shenzhen, China</td>
<td>Wuzhoulong EV bus</td>
<td>Cell over charge</td>
</tr>
<tr>
<td>7</td>
<td>2016.01</td>
<td>Brokeland., Norway</td>
<td>Tesla Model S</td>
<td>Pack external short</td>
</tr>
</tbody>
</table>
1.2 Literature review

The lessons learnt from the accidents remind us that the safety of the battery system is of critical importance. State-of-the-art research for fault diagnosis and corresponding real-application engineering solutions are listed and discussed in this section.

First, the most straightforward and most commonly applied fault diagnosis method is the threshold-based method [33, 34]. It sets the boundary values of normal operations. Whenever the voltage, current, or temperature exceeds the limit, a fault is flagged. This method is featured by its simple mechanism and ease of implementation. Therefore, the threshold-based fault detection is dominating in real battery systems. As an example, the pseudocode for the basic threshold-based fault detection method is given below, which is based on the specification sheet for a battery cell in Table 1.3.

\[
\begin{align*}
\text{if } V > 3.65 \\
&\quad \text{Flag fault: over charge} \\
\text{else if } V < 2.5 \\
&\quad \text{Flag fault: over discharge} \\
\text{if } I > 4.05 \\
&\quad \text{Flag fault: over current/external short circuit} \\
\text{if } T > 50 \\
&\quad \text{Flag fault: over heat/high temperature} \\
\text{else if } T < 0 \\
&\quad \text{Flag fault: low temperature}
\end{align*}
\]

Xiong et al. followed the method and validated through experiments that the over discharge fault can be identified by the unusual increase in temperature and unusual decrease in voltage [35]. Because of the simple algorithm of the threshold-based methods, adoption of the method in real applications guides the selection of the threshold values.

A more comprehensive threshold-based internal short circuit (ISC) detection is presented by Asakura et al. in a US patent [36]. It characterized the ISC with abnormal voltage drop recovery, high current flow and high temperature rise. Hence,
Table 1.3: Specification for a battery cell.

<table>
<thead>
<tr>
<th>Battery cell type</th>
<th>Cylindrical 18650</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nominal voltage</td>
<td>3.2 V</td>
</tr>
<tr>
<td>Charge voltage</td>
<td>3.65 V</td>
</tr>
<tr>
<td>Discharge cut-off voltage</td>
<td>2.5 V</td>
</tr>
<tr>
<td>Max pulse discharge</td>
<td>4.05 A</td>
</tr>
<tr>
<td>Operation temperature</td>
<td>0°C-50°C</td>
</tr>
</tbody>
</table>

The information in the voltage drop recovery, current, and temperature information were combined, and ISC was determined when all the conditions were met.

The inherent disadvantage of the threshold-based method is its ignorance of the battery input. The resultant drawback is that when the measured quantities do not exceed the preset boundary values, the fault will not be flagged. For example, on the initial stage of the ISC, a voltage drop-recovery can be found in the voltage measurement. However, even if this abnormal variation in voltage can be seen with the naked eyes, it cannot be detected by the threshold-based fault detection method, because the variation may not exceed the voltage limit [37].

The model-based fault detection method compensates for this drawback by taking the current input into consideration. The prerequisite of this detection method is an accurate battery model which can predict the voltage output based on the present input and past input/output. Then the model output is compared with the system output. If the residue is not reasonably small, a fault will be flagged.

Singh et al. proposed a model-based condition monitoring in lithium ion batteries [38]. Nonlinear battery parameters were estimated from experiments for batteries in healthy conditions. Then, banks of extended Kalman filters were applied to identify the dynamics of the battery online. Finally, the over charge and over discharge faults were identified based on the change in the operational characteristics of the battery in real time.

Feng et al. conducted research on early ISC detection with a high-fidelity battery model, which can predict the voltage and temperature of a battery [39]. The internal parameters of the batteries were identified online with the recursive least
squares algorithm. A detection method was presented to identify an ISC fault by the changes in the estimated parameters, i.e., the resistance and capacitance values in the equivalent circuit model (ECM) combined with the temperature derivative of equilibrium potential.

Ouyang et al. conducted experiments to investigate the influence of short circuit resistance to the identifiability of the ISC [40]. The parameter effects and the depleting effect of ISC were discussed. The results showed the direct threshold on voltage may not be a good indicator when the short resistance is not sufficiently low, because the parameter effects were hard to observe. Based on the analysis, this problem can be solved by estimating the total difference in open circuit voltage (OCV) of the cells, or the depleting effect.

Apart from the cell fault, the sensor fault detection is also critical, because all fault diagnosis depends on the sensor measurements. Liu et al. presented a systematic model-based fault diagnosis scheme to identify the sensor fault in automotive applications [41]. The key idea was to use the battery model as the analytical redundancy and identify faults with sequential residual generation using structural analysis theory and statistical inference residual evaluation.

It can be inferred from the related literature that state-of-the-art fault detection methods are mainly based on the analytical redundancy. An analytical redundancy offers a state or output to compare with that of the real battery. When the residue is close to zero, then the battery is in normal condition. The common drawbacks for the analytical-redundancy-based fault detection are

i) An accurate model is required where extensive experiment, modeling and validation work are necessary.

ii) When a fault is flagged, it may be caused by a true fault or a model discrepancy, which cannot be distinguished.

iii) The recursive online parameter update requires large computation power.

iv) The online parameter estimation for all the battery cells in a battery pack is impractical, but otherwise the inconsistencies among the cells may lead to false positive fault detection.
v) When a residue triggers a fault warning, the sensor/cell fault detection actually depends on which reading is trusted. If the sensor reading is trusted, a cell fault is flagged, otherwise a sensor fault is flagged, in other words, the sensor/cell fault cannot be distinguished.

1.3 Outline of the thesis

This thesis aims to address the drawbacks of the existing battery system fault detection methods and to provide different fault diagnosis solutions to improve the safety of electrified vehicles. The thesis is organized as follows,

The threshold-based fault diagnosis methods are first studied comprehensively by experiments in Chapter 2 for common electric faults in electrified vehicles, including over charge, over discharge, external short circuit (ESC) and ISC. The results are analyzed and recommendations are provided for online implementation.

Chapter 3 introduces the model-based fault diagnosis method and improves the method with continuous-time system identification methods. These methods demonstrate more robust fault detection for lithium ion battery packs in real applications, where the storage resolution is limited and the system dynamics is stiff.

Chapter 4 presents a correlation-based fault diagnosis method for electrified vehicles. This method does not require a battery model, which overcomes the drawbacks i), ii) and iii) of the model-based detection methods discussed in Sec. 1.2. Moreover, the applied correlation coefficient is not sensitive to battery inconsistencies, and solves problem iv) of the model-based methods.

Chapter 5 illustrates an interleaved measurement method, which can distinguish between battery failure and cell failure with negligible increase in system cost. This work compensates drawback v) of the model-based method.

Chapter 6 demonstrates the viability of integrating the interleaved voltage measurement method with the correlation-based short circuit detection method, thus realizing the advantages of both.

Finally, Chapter 7 includes the conclusion and future work.
Chapter 2

Threshold-based fault diagnosis

2.1 Introduction

This chapter introduces the basic threshold-based fault diagnosis method. This method identifies the electric faults by direct readings from voltage, current or temperature measurements. The fault alarms are triggered and distinguished by comparing the measurements with the preset threshold values.

The threshold-based methods are easy to implement and the computation effort is acceptable in most of the onboard microprocessors. As a result, this method is most widely enforced in the commercially available BMSs across the world. As an example, the basic threshold-based fault diagnosis is required in the Chinese technical specification of BMS for EVs issued in 2016, in which the cell temperature, voltage, consistency, current, isolation resistance and SoC are to be examined [42].

This chapter comprehensively studies the electrical behavior of lithium ion batteries under electric fault conditions, including over charge, over discharge, ESC and ISC. The study lays the foundation of building the integrated threshold-based fault diagnosis algorithm for the aforementioned electric faults, which serves as the benchmark to other fault detection algorithms studied in this thesis. The experiment platform built in this study is reused for data generation purposes for different electric faults discussed in the following chapters.
2.2 Experiment

2.2.1 The specifications of cells

The battery cell under test for ESC and ISC is shown in Figure 2.1. The cathod material of the 18650 cylindrical cell is LiFeO$_4$ (lithium ion phosphate), which has demonstrated remarkable advantage over other lithium ion batteries in chemical stability and safety [43, 44]. The key specifications of the cell are shown in Table 2.1. The rated capacity is 1.35 Ah, and the nominal voltage is 3.2 V. These cells were directly disassembled from used battery packs. Before abuse tests, they were cycled, and only those whose capacities were more than 80% of the rated value were selected for tests.

![Cell under test for ESC and ISC experiments.](image)

**Figure 2.1:** Cell under test for ESC and ISC experiments.

**Table 2.1:** Specification of cell under test for ESC and ISC experiments.

<table>
<thead>
<tr>
<th>Battery cell type</th>
<th>Cylindrical 18650</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nominal rated capacity</td>
<td>1.35 Ah</td>
</tr>
<tr>
<td>Nominal voltage</td>
<td>3.2 V</td>
</tr>
<tr>
<td>Charge voltage</td>
<td>3.65 V</td>
</tr>
<tr>
<td>Discharge cut-off voltage</td>
<td>2.5 V</td>
</tr>
<tr>
<td>Max continuous discharge</td>
<td>2.7 A</td>
</tr>
<tr>
<td>Max pulse discharge</td>
<td>4.05 A</td>
</tr>
</tbody>
</table>

The battery cell under test for over charge and over discharge tests is shown in Figure 2.2. To achieve more meaningful results for over charge and over discharge experiments, new 18650 cells were obtained from the same cell manufacturer. Due to the product update, the new cells have a cover in different color and slightly enhanced performance. The specifications of the updated product are shown in Table 2.2.
**Table 2.2**: Specification of cell under test for over charge and over discharge experiments.

<table>
<thead>
<tr>
<th>Battery cell type</th>
<th>Cylindrical 18650</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nominal rated capacity</td>
<td>1.4 Ah</td>
</tr>
<tr>
<td>Nominal voltage</td>
<td>3.2 V</td>
</tr>
<tr>
<td>Charge voltage</td>
<td>3.65 V</td>
</tr>
<tr>
<td>Discharge cut-off voltage</td>
<td>2.0 V</td>
</tr>
<tr>
<td>Max continuous discharge</td>
<td>2.8 A</td>
</tr>
<tr>
<td>Max pulse discharge</td>
<td>7 A</td>
</tr>
</tbody>
</table>

**2.2.2 External short circuit setup**

The test bench for ESC is developed, as shown in Figure 2.3. The test bench mainly consists of two parts: 1) cell test circuit and 2) control and data acquisition system. The test circuit is an external shorted circuit with a relay. The relay is controlled by dSPACE 1104, and can be set to be close or open. In the ESC experiments, the cell terminal voltage is measured by dSPACE 1104 analog to digital converter (ADC) with 10 V range and 12 bits resolution. Circuit loop current is measured by LEM LF 205-S/SP1 current transducer with 420 A range and 0.4 A accuracy. Both cell surface temperature and room temperature are measured by US sensor PS502-J2 thermistor with a range of -80 °C to 150 °C and 0.1 °C accuracy. All the three measurements are captured at the rate of 10 Hz.

In the ESC experiments, the resistance in the shorted loop is critical for charactering the performance of an ESC fault. In order to minimize the external resistance, all the wires are designed to be as short as possible as shown in Figure 2.4. The resistance of all the circuit components, including relay, conducting wire, battery end
Figure 2.3: Schematics for ESC test bench.

connection, is 3.3 mΩ, which is less than 1/5 of the cell internal resistance (17 mΩ). In these experiments, the SoCs of the cells ranges from 20% to 100% at a step of 10%.

To ensure safe operation, the test circuit is isolated inside a test box made of metal. The inside view of the box is shown in Figure 2.4. The relay is fixed at the bottom of the box. The current sensor and the cell under test are lifted up with pieces of a fireproof fiberglass board. This design can prevent the heat directly flowing through the aluminum case and keep the wires short. The duration of the short circuits is 1800 s.

Figure 2.4: Experiment setup for ESC experiments.
2.2.3 Internal short circuit setup

The ISC test bench is designed to simulate a type of physical damage to battery cells that may occur in car accidents. The test procedure is demonstrated in Figure 2.5. A press drill is used to penetrate the battery, and the drill is left inside the cell to model a battery cell being internally shorted by foreign conducting objects.

Figure 2.5: Operation procedure for ISC experiments.

In the ISC experiments, no external circuits are connected to the test cell. The voltage is measured by dSPACE 1104 ADC with 10 V range and 12 bits resolution, and both cell surface temperature and room temperature are measured by US sensor PS502-J2 thermistor with a range of -80 °C to 150 °C and 0.1 °C accuracy. The data are captured at the rate of 10 Hz.

To ensure safe operation during testing, the whole test bench is placed into a temperature controlled chamber. The drill operation is externally controlled. After penetrating the cell to a desired depth, the drill is unfastened from the press drill and left inside the cell until experiments are completed. The figures for the experiment setup are given in Figure 2.6.

The penetration depth is 5 mm and the experiments are conducted to cells with 0% to 100% SoC at the step of 10%.

2.2.4 Over charge and over discharge setup

The test bench for over charge and over discharge is shown in Figure 2.7. An Arbin BT-2000 is used as the battery cycler to charge and discharge the test cells. The voltage range for measurement is 0 V to 10 V with 11 bits resolution. The current range is 100 A with 0.6 mA accuracy. The temperature measurement range is -200 °C to 400 °C with 1 °C accuracy.
Figure 2.6: Experiment setup for ISC experiments.

Figure 2.7: Experiment setup for over charge and over discharge experiments.

For the over charge experiments, the test cells are prepared with 100% SoC and should be rested for at least one hour. The cells are then over charged from 3.65 V (maximum charge voltage) to 4.65 V by the step of 0.1 V. Every time the terminal voltage reaches a voltage step, the charge process will be suspended, and EIS measurements will be taken after one hour of rest. The over charge experiments are conducted with varying charge currents. The currents range from 0.5C to 2C rate at the step of 0.5C rate, where C is a multiple of the current that a battery can sustain for one hour.
2.3 Results

2.3.1 Threshold-based fault diagnosis

Based on the empirical results provided in the previous section, a threshold-based preliminary diagnosis algorithm is postulated, as shown in Figure 2.8.

![Proposed fault diagnosis algorithm for electric faults.](image)

**Figure 2.8:** Proposed fault diagnosis algorithm for electric faults.

The occurrence of electric faults is determined by comparing the battery status with the predefined threshold values in voltage, current and temperature, $V_{\text{ESC}}$, $(\frac{dT}{dt})_{\text{ESC}}$, $I_{\text{ESC}}$, $V_{\text{OC}}$, $(\frac{dV}{dt})_{\text{ISC}}$, $(\frac{dT}{dt})_{\text{ISCl}}$, $(\frac{dT}{dt})_{\text{ISCh}}$, and $V_{\text{OD}}$. The over charge and over discharge threshold values can be determined based on their definitions. There exist other threshold values, where $V_{\text{OD}}$ is the voltage lower limit to determine ESC, $(\frac{dT}{dt})_{\text{ESC}}$ is the temperature increase rate upper limit to determine ESC, $I_{\text{ESC}}$ is the upper current limit to determine ESC, $V_{\text{OC}}$ is the upper voltage limit to determine over charge, $(\frac{dV}{dt})_{\text{ISC}}$ is the voltage decrease rate lower limit to determine ISC, $(\frac{dT}{dt})_{\text{ISCl}}$ and $(\frac{dT}{dt})_{\text{ISCh}}$ are the lower and upper boundary temperature increase rate values to determine ISC, and $V_{\text{OD}}$ is the lower voltage limit to determine over discharge. All the values are determined in this section based upon empirical results.

2.3.2 External short circuit

The current, voltage and temperature responses of 1800 s ESC experiments are shown in Figures 2.9, 2.10 and 2.11, respectively. The current increases sharply at the beginning of ESC, then drops to a plateau, and finally gradually drops to zero.
Figure 2.9: Current responses for ESC experiments.

Figure 2.10: Voltage responses for ESC experiments.

The voltage drops to zero when the relay is closed, and when the relay is opened, some of the voltage can be restored to a certain value. The temperature increases
gradually until reaching its maximum and then drops down due to natural cooling.

From Figure 2.10, when ESC occurs, the terminal voltage for battery cells goes to almost zero due to low output resistance, whereas the minimum discharging voltage for the selected cell is 2.5 V. The maximum voltage when the relay is closed during the experiments is 0.3 V. This lower voltage limit is selected to be the lower voltage limit $V_{ESC}$ that determines ESC.

The temperature increase rates, i.e. $\frac{dT}{dt}$, for different cells in ESC experiments are plotted in Figure 2.12. The temperature increase rates are different with different initial SoCs. For the experiment with the lowest maximum increase rate in the figure (0% SoC), the maximum temperature increase rate can go up to more than 0.5 $^\circ$C/s. The temperature increase rate at the extreme discharge operation is examined by discharging the battery with the maximum current. The results are shown in Table 2.3. From Figure 2.12 and Table 2.3, the temperature increase rates in ESC conditions are 100 times more than that of normal operations. A proper value needs to be determined for ESC detection at an early stage. We selected half of the maximum $\frac{dT}{dt}$ for the 0% SoC ESC experiment to be the threshold. Thus, $(\frac{dT}{dt})_{ESC}=0.25$ $^\circ$C/s.

From Figure 2.9, the maximum current at the instant ESC occurs can be

![Figure 2.11: Temperature responses for ESC experiments.](image_url)
above 50 A, which is more than 37C rate, while the maximum pulse discharge rate is only 3C. According to the definition, an ESC happens when the current goes beyond its maximum allowable operation current. In this case, 4.05 A is selected to be the current upper limit $I_{ESC}$ to determine the occurrence of ESC.

### 2.3.3 Internal short circuit

The temperature and voltage responses of 5 mm ISC experiments are shown in Figure 2.13 and Figure 2.14, respectively. The temperature rises gradually after ISC is induced, while the voltage drop delays for a certain period of time after the cell has been internally shorted. It needs to be noted that, for some cases in the 5 mm
ISC experiments (60% and 80%), the maximum temperature was achieved before the voltage drops could be observed.

When ISC occurs, the temperature increase rate depends on the SoC of the
battery cells, as shown in Figure 2.15. The temperature increase rate of 30% SoC in 5 mm ISC experiment had the lowest maximum value. The temperature increase rate threshold value is determined to be half of this value, thus \( \frac{dT}{dt}_{ISC} \) is 0.035 °C/s.

![Figure 2.15: Temperature increase rate for ISC experiments.](image)

The upper temperature increase rate threshold, i.e., \( \frac{dT}{dt}_{ISC} \) is designed to distinguish the temperature responses of ISC from ESC. However, from Figure 2.12 and Table 2.4, an overlap exists between their maximum temperature increase rates, which means that, without additional information, no proper value can be selected to separate ISC from ESC. Therefore, the SoC of cells under electric faults can be introduced in the fault detection algorithm, i.e. \( \frac{dT}{dt}_{ISC} = f(\text{SoC}) \). This method makes the system require careful calculation, and the distinction cannot be made until the temperature increase rate difference is captured, which is tens of seconds after fault occurrence. The second method is to use voltage decrease rate \( |\frac{dV}{dt}| \).

In the experiment setup, no load was applied to the cell when ISC was induced. Thus, by comparing Figure 2.13 and the inset in Figure 2.10, a proper value of \( |\frac{dV}{dt}| \) can be selected to distinguish between ISC and ESC. In ESC, the \( |\frac{dV}{dt}| \) can be as high as 15 V/s, while according to Table 2.5, the maximum voltage decrease rate is less than 0.3 V/s. Thus, \( |\frac{dV}{dt}|_{ISC} \) is selected to be half of the voltage decrease
reading, 0.0115 V/s.

**Table 2.4**: Maximum $\frac{dT}{dt}$ in different ISC experiments.

<table>
<thead>
<tr>
<th>SoC</th>
<th>$\frac{dT}{dt}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>20%</td>
<td>0.1035 °C/s</td>
</tr>
<tr>
<td>30%</td>
<td>0.0705 °C/s</td>
</tr>
<tr>
<td>40%</td>
<td>0.1043 °C/s</td>
</tr>
<tr>
<td>50%</td>
<td>0.1579 °C/s</td>
</tr>
<tr>
<td>60%</td>
<td>0.3131 °C/s</td>
</tr>
<tr>
<td>70%</td>
<td>0.1040 °C/s</td>
</tr>
<tr>
<td>80%</td>
<td>0.1134 °C/s</td>
</tr>
<tr>
<td>90%</td>
<td>0.1267 °C/s</td>
</tr>
<tr>
<td>100%</td>
<td>0.1392 °C/s</td>
</tr>
</tbody>
</table>

**Table 2.5**: Maximum $|\frac{dV}{dt}|$ in different ISC experiments.

| SoC | $|\frac{dV}{dt}|$ |
|-----|--------------------|
| 20% | 0.0229 V/s        |
| 30% | 0.0337 V/s        |
| 40% | 0.0466 V/s        |
| 50% | 0.0332 V/s        |
| 60% | 0.0452 V/s        |
| 70% | 0.0921 V/s        |
| 80% | 0.0564 V/s        |
| 90% | 0.0320 V/s        |
| 100%| 0.0498 V/s        |
2.3.4 Over charge and over discharge

The voltage and SoC increases for the 0.5C over charge experiments are shown in Figure 2.16. The maximum SoC is 106.5%, and the corresponding maximum over charge voltage is 4.65 V, which is 1 V above the maximum charge voltage defined in the specification sheet. Every time the voltage is over charged by a voltage step of 0.1 V, the over charge will be paused, and the cell will rest for one hour. During the rest periods, the voltage drops and approaches closer to OCV.

![Graph showing voltage and SoC increase for over charge experiments.](image)

**Figure 2.16:** Voltage and SoC increase for over charge experiments.

The current and temperature responses for the 0.5C over charge experiments are shown in Figure 2.17. This figure shows that the temperature does not have a close relationship with input current in over charge experiments.

Similar results for over discharge experiments are shown in Figure 2.18 and Figure 2.19.

Over charge happens when an excess of charges is stored in the battery cell. From the charging point of view, a maximum charging voltage is usually specified by the manufacturer. When this charging voltage is achieved during the charging process, this voltage is maintained, but never exceeded, to protect the battery from
storing excessive charges. Based on this important data, the maximum charging voltage for the cell defined in the specification sheet is 3.65 V. The upper voltage

![Graph](image1.png)

**Figure 2.17:** Current and temperature responses for over charge experiments.

![Graph](image2.png)

**Figure 2.18:** Voltage and SoC increase for over discharge experiments.
Figure 2.19: Current and temperature responses for over discharge experiments.

A similar principle is also valid for over discharge, thus the lower voltage limit $V_{OD}$ for over discharge determination is 2.0 V.

From Figure 2.17 and Figure 2.19, the temperature response of the cells is not sensitive to over charge and over discharge. Therefore, temperature is not selected to be one of the measurements that determines over charge and over discharge.

2.4 Discussion

2.4.1 Temperature versus temperature increase rate

In order to determine whether to use direct $T$ measurements or $T$ variation rate, i.e., $\frac{dT}{dt}$, as the threshold in the logic diagram, comparison experiments are conducted for ESC faults.

In these experiments, the battery cells are first charged to 90% SoC. Then a number of consecutive UDDS cycles are scaled to the single cell level and applied to the battery cells. When the SoC of the cells achieves certain values, a close command
will be sent to the relay and ESC will occur consequently. Based on the voltage, temperature and current measurements, it is compared whether $T > 50 \, ^\circ C$ or $\frac{dT}{dt} > 0.25 \, ^\circ C/s$ will detect the fault earlier. It needs to be noted that $50 \, ^\circ C$ is the maximum operation temperature for the cell, as shown in Table 2.1.

The measurements of an 80% SoC ESC validation experiment are shown in Figure 2.20. At 970.8 s, the relay is closed. The temperature of the cell then increases, the voltage drops, and the current increases. The logic signals for each of these conditions are shown in Figure 2.21. At the same instant when the relay is closed, the conditions for voltage and current are met. Since the detection conditions are operated by the AND operator, when the third condition is met, the fault will be detected. After 4.9 s, the temperature increase rate condition is met; however, it takes 26.1 s for the temperature to go beyond $50 \, ^\circ C$, which is almost 5 times as long as it takes using the temperature increase rate detection method.

**Figure 2.20:** Comparison between $T$ and $\frac{dT}{dt}$ detection time.

A detailed temperature plot during fault detection is shown in Figure 2.22. The $T$ method not only takes a longer time in fault detection, but the cell is also at a higher temperature when the detection occurs, which has a negative effect on fault mitigation. More comparison results at different SoC can be found in Table 2.6. The
time that each method takes to detect an ESC fault is listed and compared to the time duration between the fault occurrence and the maximum $T$ is observed. The rise in temperature at fault detection is also listed, and compared to the maximum increase in temperature in the whole experiments. This table shows that $\frac{dT}{dt}$ method is better than $T$ method in that the $\frac{dT}{dt}$ method is able to detect an ESC fault with less time duration and less increase in temperature.

![Figure 2.21](image_url) Logic signal for each of the detection conditions for ESC.

**Table 2.6:** Comparison results at different SoC.

<table>
<thead>
<tr>
<th>SoC</th>
<th>$\frac{dT}{dt}$ method</th>
<th>$T$ method</th>
<th>$T$ increase duration</th>
<th>Time percentage</th>
<th>Total $T$ rise</th>
<th>$T$ percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>20%</td>
<td>9.9 s</td>
<td>48.4 s</td>
<td>133.3 s</td>
<td>7.4%</td>
<td>45.61 °C</td>
<td>3.0%</td>
</tr>
<tr>
<td>30%</td>
<td>6.1 s</td>
<td>33.7 s</td>
<td>108.7 s</td>
<td>5.6%</td>
<td>73.04 °C</td>
<td>1.3%</td>
</tr>
<tr>
<td>40%</td>
<td>3.9 s</td>
<td>28.4 s</td>
<td>88.9 s</td>
<td>4.4%</td>
<td>83.55 °C</td>
<td>0.92%</td>
</tr>
<tr>
<td>50%</td>
<td>6.0 s</td>
<td>35.9 s</td>
<td>104.6 s</td>
<td>5.7%</td>
<td>68.91 °C</td>
<td>1.2%</td>
</tr>
<tr>
<td>60%</td>
<td>4.1 s</td>
<td>29.0 s</td>
<td>96.3 s</td>
<td>4.3%</td>
<td>83.93 °C</td>
<td>1.0%</td>
</tr>
<tr>
<td>70%</td>
<td>3.7 s</td>
<td>25.9 s</td>
<td>96.6 s</td>
<td>3.8%</td>
<td>85.74 °C</td>
<td>0.86%</td>
</tr>
<tr>
<td>80%</td>
<td>4.9 s</td>
<td>26.1 s</td>
<td>91.9 s</td>
<td>5.3%</td>
<td>74.32 °C</td>
<td>1.2%</td>
</tr>
</tbody>
</table>
2.4.2 Resistance increase on over charge/discharge stages

As shown in Figure 2.16 and Figure 2.18, the voltage jump upon charge or discharge increases as the cell is over charged/discharged more. The rate current in both processes are the same, which indicates that the internal resistances are increased in the over charge/discharge stages.

A experiment is conducted with six battery cells connecting in series, and they are charged from 0% SoC to 4.65 V. Their voltage responses in Figure 2.23 show that the cells are over charged after around 7000 s. Their corresponding temperature responses are given in Figure 2.24. The cell temperature increases sharply as the cells are over charged. However, the temperature increase in internal resistance is not reliable in fault diagnostic, because the little variation (less than 3 °C) is within noise and tolerance levels, making it not robust as an indicator.

2.5 Summary

In this chapter, a threshold-based fault detection algorithm is introduced in detail for the battery system, i.e., when certain conditions are met, a certain features
are flagged, and a logic combination of features trigger a fault alarm. Abundant experiments are conducted to obtain the fault data to capture the electric and thermal
behaviors, and the features on voltage, current and temperature are used as indicators to identify electric faults.

The advantages of the threshold-based fault detection algorithm are

i) The computation cost for the threshold-based detection is low, and it can be easily applied to low-cost microchips.

ii) The threshold-based method never gives false positive faults.

iii) In over charge/discharge faults, the method measures the voltage value, which is the direct indicator for the two electric faults based on their definition. This ensures the simple and robust fault identification.

The disadvantages of the threshold-based method are

i) In real applications, some of the measurement may not be available. For example, when ESC occurs, the current may not flow through the current sensor and thus the method may flag false negative faults.

ii) The condition for ESC and ISC may vary in real situations. For example, the resistance in the ESC loop may be larger, and the temperature increase rate may vary. The property of the foreign objects in the ISC or the depth of the damage may also vary, making the a fixed threshold value impossible to cover all situations.

iii) The threshold-based method may indicate false negative fault even if all the measurements are within normal operation range. This usually happens at the initial phase of an internally induced ISC fault [37].

This chapter is based on the following published papers,


B. Xia, C. Mi, Z. Chen, B. Robert, “Multiple cell lithium ion battery system electric fault online diagnostics”, *IEEE Transportation Electrification Conference and Expo*, 2015.
Chapter 3

Model-based fault diagnosis

3.1 Introduction

Generally, the existing fault diagnosis methods are redundancy-based, which can be further distinguished into hardware redundancy and analytical redundancy. The key idea is to compare the output/state of the target system with that from a second source.

The hardware redundancy utilizes duplicative components sharing same input to provide the value to compare with, and flags a fault when the difference between the outputs is not reasonably small [45, 46]. In most cases, three duplicative components are needed to implement the “majority vote” algorithm, such that the fault location can be isolated. The key disadvantages of the hardware redundancy is its increases in system cost and complexity, which prevent its application in battery systems.

The analytical redundancy builds a mathematical system model, and uses the model to calculate the output/state of the system. Then the value can be compared with that of the true system [47, 48, 49]. Indeed, the threshold-based fault diagnosis method introduced in Chapter 2 can be regarded as the model-based fault diagnosis with a simple model, which only describes the system limit and captures its behavior under certain extreme conditions. A major disadvantage is that the simple model does not take the input of the battery cell into consideration. In other words, if the system states are within its safe operation limit, the simple model cannot tell the fault condition. For example, if an ISC occurs, but the voltage does not drop lower
than the minimum discharge voltage, then the threshold-based method alone will not be able to flag the fault [50]. Thus, a complete model is required to ensure more accurate fault identification.

This chapter introduces a continuous-time (CT) system identification method which can accurately identify the parameters of a lithium ion battery. Due to the “stiff” nature of the battery cells, this method is more robust in online implementation compared with the traditional discrete-time (DT) system identification methods. The accurate model can then be applied to predict the battery behavior in normal condition. If the battery status is different from the normal conditions, a fault flag can be flagged. The battery modeling work serves as the basis of model-based fault detection and the results are compared with that of the threshold-based detection method.

3.2 Battery modeling

3.2.1 Equivalent circuit model

Among the most commonly applied modeling approaches, the electrochemical model provides high accuracy in estimation since it originates from the first principles of underlying electrochemistry [51]. However, the accurate estimation is achieved at the cost of high complexity in data processing, which requires a significant amount of memory space and computational power to cope with partial differential equations and unknown parameters. This makes this method impractical in real-time applications.

In contrast, the ECM is widely accepted in the application level because of its simplicity and ease in online implementation [52]. Equivalent circuit modeling utilizes the system identification techniques to relate the input and output behavior of the battery with circuit elements. An $n^{th}$-order ECM of lithium ion batteries is shown in Figure 3.1. The $n$-RC networks can be interpreted as various time domain characteristics of the physical processes and chemical reactions within the battery cell, the series resistance $R_0$ is the internal resistance of the battery, and the voltage source represents the electrochemical equilibrium potential at different states, also known as OCV [53].
Figure 3.1: $n$th-order ECM for lithium ion batteries.

All the aforementioned ECM parameters change as SoC changes, but the parameters can be regarded as constant when SoC variation is small, especially in the carefully designed characterization profiles. The battery characterization determines the best estimates of all the parameters at different SoCs. In general, the OCV is obtained by experiments, and the current and voltage responses in the hybrid pulse power characterization (HPPC) test are used to determine the values of $n$-RC networks and $R_0$ at different SoCs [54].

### 3.2.2 Parameter identification of battery models

#### Continuous-time battery model

The CT transfer function of the $n$th-order ECM depicted in Figure 3.1 can be written as

$$H(s) = \frac{V_{OCV}(s) - V_{batt}(s)}{I(s)} = \frac{V(s)}{I(s)}$$

$$= \frac{R_1}{R_1C_1s + 1} + \frac{R_2}{R_2C_2s + 1} + \cdots + \frac{R_n}{R_nC_ns + 1} + R_0$$

where $V_{OCV}(s) = \mathcal{L}\{v_{OCV}(t)\}$, $V_{batt}(s) = \mathcal{L}\{v_{batt}(t)\}$, $I(s) = \mathcal{L}\{i(t)\}$, and $\mathcal{L}\{\cdot\}$ is the notation for the Laplace transform.

This function can be rewritten as

$$(s^n + a_1s^{n-1} + \cdots + a_{n-1}s + a_n)V(s) = (b_0s^n + \cdots + b_{n-1}s + b_n)I(s)$$

(3.2)
where all the coefficients are functions of the unknown circuit parameters. Define
\[
\theta = [a_1 \cdots a_{n-1} a_n b_0 \cdots b_{n-1} b_n]^T
\]
where \( f : \mathbb{R}^{2n+1} \rightarrow \mathbb{R}^{2n+1} \) maps the circuit parameters to the equation unknowns.

Equation (3.2) can be directly written into a regression form as
\[
v^{(n)}(t) = \varphi(t)\theta
\]
where \( v^{(n)}(t) \) denotes the \( n \)th time-derivative of \( v(t) = v_{OCV}(t) - v_{batt}(t) \), and \( \varphi(t) \) is the regression vector given by
\[
\varphi(t) = [-v^{(n-1)}(t) \cdots -v(t) i^{(n)}(t) \cdots i(t)]
\]

In practice, the measured terminal voltage of batteries is usually contaminated by noises. Therefore, an equation error \( e(t) \) is added to the given regression form. Thus a complete model is given by
\[
v^{(n)}(t) = \varphi(t)\theta + e(t)
\]

**Discrete-time battery model**

To obtain the DT battery model, by using the correct piecewise constant assumption for the current input in HPPC tests, the zero-order hold (ZOH) equivalent of (3.1) can be derived by (3.7).

\[
H(z) = (1 - z^{-1}) \mathcal{Z} \left\{ \frac{H(s)}{s} \right\}
\]

where \( \mathcal{Z} \{ \cdot \} \) is the notation for the \( z \)-transform.

Thus the CT transfer function (3.1) yields to
\[
H(z) = \frac{V(z)}{I(z)} = \frac{R_1(1 - e^{-\frac{T_s}{R_1C_1}})}{z - e^{-\frac{T_s}{R_1C_1}}} + \frac{R_2(1 - e^{-\frac{T_s}{R_2C_2}})}{z - e^{-\frac{T_s}{R_2C_2}}} + \cdots + \frac{R_n(1 - e^{-\frac{T_s}{R_nC_n}})}{z - e^{-\frac{T_s}{R_nC_n}}} + R_0
\]

and it can be rewritten as
\[
(1 + c_1 z^{-1} + \cdots + c_n z^{-n})V(z) = (d_0 + d_1 z^{-1} + \cdots + d_n z^{-n})I(z)
\]
where \( T_s \) is the sampling interval, and the coefficients in (3.9) are functions of the unknown parameters as well as \( T_s \). Define

\[
\theta_d = [c_1 \cdots c_n \ d_0 \ d_1 \cdots d_n]^T
\]

\[
= g(R_1, \cdots, R_{n-1}, R_n, C_1 \cdots, C_{n-1}, C_n, R_0, T_s)
\]

(3.10)

where \( g: \mathbb{R}^{2n+2} \to \mathbb{R}^{2n+1} \) maps the circuit parameters and \( T_s \) to the unknowns.

The regression form of (3.9) with a noise term \( \epsilon(k) \) can be written as

\[
v(k) = \varphi_d(k) \theta_d + \epsilon(k)
\]

(3.11)

where

\[
\varphi_d(k) = [-v(k-1) \cdots -v(k-n) \ i(k) \ i(k-1) \cdots i(k-n)]
\]

(3.12)

and \( v(k) \) denotes the sampled value of \( v(t) \) at time-instant \( t_k \).

### 3.2.3 System identifiability

The structural identifiability describes the uniqueness of parameters given a dynamic model with noise-free and persistent excitations [55, 56]. The battery system is globally identifiable if there is a unique solution \( \theta, \theta \in \Theta \subset \mathbb{R}^{2n+1} \), for (3.6) and (3.11); the system is locally identifiable if there are a finite number of solutions in \( \Theta \); the system is unidentifiable if there are an infinite number of solutions in \( \Theta \).

The identifiability of Randles ECMs are discussed in [57]. The \( n \)th-order ECM discussed in this paper has similar structure as that of the Randles models, except for an additional capacitor connecting in series with the RC networks. Similar derivations hold for the ECM of interest in this paper as well.

Given the continuous system transfer function as (3.1), if two sets of circuit parameters lead to the same transfer function of an ECM, then

\[
\frac{R_1}{R_1 C_1 s + 1} + \cdots + \frac{R_n}{R_n C_n s + 1} + R_0 = \frac{R_1^*}{R_1^* C_1^* s + 1} + \cdots + \frac{R_n^*}{R_n^* C_n^* s + 1} + R_0^*, \text{ for all } s
\]

(3.13)

A necessary condition for (3.13) to hold is

\[
(s + \frac{1}{R_1 C_1}) \cdots (s + \frac{1}{R_n C_n}) = (s + \frac{1}{R_1^* C_1^*}) \cdots (s + \frac{1}{R_n^* C_n^*}), \text{ for all } s
\]

(3.14)
Since an \( n \) degree polynomial is uniquely characterized by its \( n \) distinct roots, the assignments of \((-\frac{1}{R_1C_1}, \ldots, -\frac{1}{R_nC_n})\) in (3.14) need to be the permutations of \((-\frac{1}{R_1C_1}, \ldots, -\frac{1}{R_nC_n})\). Assume the order of the distinct roots is strictly defined, i.e. \( R_1C_1 < \cdots < R_nC_n \) and \( R_1^*C_1^* < \cdots < R_n^*C_n^* \). Since the functions of \( \frac{1}{(s + \frac{1}{R_iC_i})} \) in (3.14) are linear independent, \( R_iC_i = R_i^*C_i^* \) can be obtained and consequently \( R_i = R_i^* \) from (3.13) for \( i = 1, 2, \cdots, n \). Therefore, all the parameters in the model structure of (3.1) are uniquely determined. The one-to-one mapping of \( f \) in (3.3) ensures the uniquely determined \( \theta \) in the reparametrization.

Similar derivation holds for discrete time ECM identifiability. Therefore, the conclusion can be drawn that both CT and DT \( n \)th-order ECMs are globally identifiable when the order of the RC networks is strictly defined.

### 3.2.4 Sensitivity of discrete-time model poles

The time-constants of an ECM describe essential system properties of the circuit. Physically, they give the time domain characteristics of voltage variations due to different chemical or physical processes upon charge and discharge. The time-constants \( \tau_i \) in the ECM are calculated by

\[
\tau_i = R_iC_i, \quad i = 1, 2, \cdots, n 
\]  

(3.15)

Note that the time-constants are closely related to the eigenvalues, or pole locations of the system as

\[
\tau_i = \frac{1}{|\lambda_i|}, \quad i = 1, 2, \cdots, n 
\]  

(3.16)

where \( \lambda_i \) is the \( i^{th} \) eigenvalue of the system.

In order to characterize the fast dynamics of a system, the sampling frequency should be high enough. A rule of thumb [58] is to select a sampling time such that

\[
f_s \geq 2 \times \frac{1}{\tau_{\min}} \iff |\lambda_{\max}| T_s \leq \frac{1}{2}
\]

(3.17)

where \( \lambda_{\max} \) is the largest eigenvalue, \( \tau_{\min} \) is its corresponding smallest time-constant in the system, \( T_s \) is the sampling time and \( f_s \) is the sampling frequency. In practical applications, the sampling frequency \( f_s \) is usually set to be higher than the boundary value of \( 2/\tau_{\min} \) to ensure sufficient sampling.
Figure 3.2: Discrete pole converges to (1, 0) in z-plane as $\lambda T_s \to 0$.

However, a high sampling rate gives rise to undesirable sensitivity issues as illustrated in Figure 3.2. It is well known that the negative real poles in the s-domain map to the interval between the origin and (1, 0) on the real axis of z-domain by (3.18). As $\lambda_i T_s \to 0$, the poles in the z-domain approaches (1, 0).

$$z_i = e^{\lambda_i T_s}$$ (3.18)

Given (3.16), the sensitivity of the CT model time-constant with respect to z-domain pole location can be derived as (3.19).

$$S = \left| \frac{z \partial \tau}{\tau \partial z} \right| = \left| \frac{e^{-\frac{T_s}{\tau}}}{\tau} \frac{\partial \tau}{\partial e^{-\frac{T_s}{\tau}}} \right| = \frac{e^{-\frac{T_s}{\tau}}}{\tau} \frac{\tau^2}{T_s e^{-\frac{T_s}{\tau}}} = \frac{1}{|\lambda|T_s} = \tau f_s$$ (3.19)

The result shows that the sensitivity is the product of sampling frequency and time-constant. Without considering the hardware cost, high sampling frequency is desired so that the DT system is a good approximation of the CT system. However, equation (3.19) implies that faster sampling yields to higher sensitivity of the DT model identification to external disturbances and computation errors.

One can also observe from (3.19) that the sensitivity is larger for larger time-constants. In a practical on-board battery monitoring system, the sampling frequency can be 100 Hz, and typical time-constant values for 2nd-order ECMs are 30 s and 1,000
Thus the sensitivities can be locally as high as 3,000 and 100,000 respectively. It indicates that a small variation in $z$-domain pole estimation leads to a significant change in time-constant estimation. In the extreme condition, as $\lambda T_s \to 0$, the sensitivity goes to infinity.

It is important to state that such a sensitivity issue stems from the discretization process, and it does not exist in the CT model identification cases.

### 3.2.5 Prescaling in fixed-point storage

Most on-board vehicular microprocessors use fixed-point data storage systems. Such representation limits the information that can be stored during calculation due to precision loss and overflow.

In the CT model identification process, given the stiffness of battery systems, the time-constants vary in one or two orders of magnitude. Since the to-be-estimated coefficients are closely related to the multiplication of different pole locations, these coefficients can be different in several orders of magnitude. If the magnitude of the coefficients is too small, it will lead to big discrepancies in storage, because of the fixed minimum resolution. In order to solve this problem, a parameter prescaling technique is used to maintain the coefficients in the same order of magnitudes, as

$$\tilde{\theta} = U\theta$$

(3.20)

where the prescaling matrix

$$U = \begin{bmatrix}
u_1 & 0 & \cdots & 0 \\
0 & u_2 & \ddots & \vdots \\
\vdots & \ddots & \ddots & 0 \\
0 & \cdots & 0 & u_{2n+1}
\end{bmatrix}$$

(3.21)

and $\theta$ is the parameter vector defined in (3.3).

For instance, if $b_n$ in $\theta$ has a magnitude in the order of $10^{-9}$, whereas the processor is 16 bits, i.e. the resolution is $2^{-16} = 1.5 \times 10^{-4}$, it is impossible to store $b_n$ in such processor for any further calculation. In this case, $u_{2n+1}$ in $U$ can be set to $10^9$ such that $u_{2n+1} b_n$ can be stored properly. Then $\theta$ can be retrieved by

$$\theta = U^{-1}\tilde{\theta}$$

(3.22)
In the DT model identification, the dominating poles are close to 1, thus the to-be-estimated coefficients have similar order of magnitudes. Therefore the prescaling is not necessary.

3.3 Continuous-time battery model identification

3.3.1 Least-squares-based SVF method

The CT model parameter can be obtained from the least squares solution of $\theta$ in (3.6). However, the time-derivatives of the input and output are usually not measured. One traditional approach to handle the time-derivatives measurement problem is to use the state variable filter (SVF) method (see e.g. [60]), which generates filtered (smoothed) versions of the required time-derivatives. A typical SVF is in the form of

$$L_n(s) = \left(\frac{\alpha}{s + \alpha}\right)^n$$

where $n$ is the highest system order, and $\alpha$ determines the cut-off frequency of the SVF. The choice of $\alpha$ is recommended to be slightly higher than the estimated bandwidth of the system [60]. Applying the SVF to (3.6) yields the linear model as (3.24).

$$v^{(n)}_{svf}(t) = \varphi_{svf}(t)\theta' + e'(t)$$

where $\varphi_{svf}(t) = [-v^{(n-1)}_{svf}(t) \cdots -v_{svf}(t) i^{(n)}_{svf}(t) \cdots i_{svf}(t)]$, $v^{(n)}_{svf}(t) = L^{-1}\{s^n L_n(s)V(s)\}$, $i^{(n)}_{svf}(t) = L^{-1}\{s^n L_n(s)I(s)\}$, and $L^{-1}\{\cdot\}$ denotes the inverse Laplace transform.

Based on $N$ sampled measurements of both input and output signals at time instants $t_k$, $k = 1,...,N$, the CT least-squares-based state variable filter (LSSVF) estimator of $\theta$ is expressed as

$$\hat{\theta}_{lssvf} = \left[ \sum_{k=1}^{N} \varphi_{svf}^T(t_k)\varphi_{svf}(t_k) \right]^{-1} \sum_{k=1}^{N} \varphi_{svf}^T(t_k)v^{(n)}_{svf}(t_k)$$

3.3.2 Improved instrumental-variable-based SVF method

The least squares solution is unbiased when the equation error is uncorrelated to the regressor, whereas this is usually not true in real applications. In other words,
\( \hat{\theta}_{lssvf} \) converges to the true parameter \( \theta_0 \) with the assumption of \( E[\varphi_{svf}^T(t_k)e'(t_k)] = 0 \), but the least squares regressor \( \varphi_{svf}(t) \) contains the measured output voltage, which correlates with \( e'(t) \) by (3.24). In order to make the CT parameter identification consistent for correlated equation errors, the instrumental variable (IV) method is introduced. The main idea of the IV method is to find an instrument \( \zeta(t_k) \) whose components are uncorrelated with \( e'(t_k) \), i.e. \( \frac{1}{N} \sum_{k=1}^{N} \sum_{k=1}^{N} \zeta_{svf}^T(t_k)e'(t_k) = 0 \) [61]. The most common IV method utilizes an auxiliary model to generate a noise-free estimate of output, as

\[
\zeta_{svf}(t_k) = [-w_{svf}^{(n-1)}(t_k) \cdots -w_{svf}(t_k) \ i_{svf}^{(n)}(t_k) \ \cdots \ i_{svf}(t_k)]
\] (3.26)

where \( w_{svf}(t_k) \) is the noise-free estimate of voltage calculated by

\[
w_{svf}(t_k) = L^{-1}\{L_n(s)H(s, \hat{\theta}_{lssvf})I(s)\}
\] (3.27)

The CT instrumental-variable-based state variable filter (IVSVF) estimator of \( \theta \) is given as

\[
\hat{\theta}_{ivsvf} = \left[ \sum_{k=1}^{N} \zeta_{svf}^T(t_k)\varphi_{svf}(t_k) \right]^{-1} \sum_{k=1}^{N} \zeta_{svf}^T(t_k)v_{svf}^{(n)}(t_k)
\] (3.28)

The flow chart for the implementation of \( n^{th} \)-order CT IVSVF battery parameter estimator is summarized in Figure 3.3.

It can be noticed that there is no further assumption or limitation of the operating conditions of batteries in CT identification, so long as the battery is in its defined normal operating range. In addition, when dealing with stiff systems, the CT identification method does not require as high storage resolution as DT identification does, because it does not involve numerically dedicate transformation. Therefore, the CT identification methods are expected to have better performance over DT methods, especially when the system is stiff and the storage resolution is limited.

### 3.3.3 Model parameterization of the 2nd-order ECM

Based on the analysis in the previous sections, the CT identification methods can be applied to an ECM with any order. In the following sections, the 2nd order ECM is selected because it is the simplest form to present a stiff system. Other than
that, [62] concludes that the 2nd order ECM is an optimum choice for implementation of most battery energy and power management strategies.

The CT parameters for the 2nd-order ECM identification are given as

\[
\begin{align*}
a_1 &= \frac{1}{R_1C_1} + \frac{1}{R_2C_2} \\
a_2 &= \frac{1}{R_1C_1R_2C_2} \\
b_0 &= R_0 \\
b_1 &= R_0 \left( \frac{1}{R_1C_1} + \frac{1}{R_2C_2} \right) + \frac{1}{C_1} + \frac{1}{C_2} \\
b_2 &= \frac{R_0 + R_1 + R_2}{R_1C_1R_2C_2}
\end{align*}
\]

For comparison purposes, the DT parameters are given as

\[
\begin{align*}
c_1 &= -\left( e^{-\frac{T_0}{R_1C_1}} + e^{-\frac{T_0}{R_2C_2}} \right) \\
c_2 &= e^{-\left(\frac{T_0}{R_1C_1} + \frac{T_0}{R_2C_2}\right)} \\
d_0 &= R_0 \\
d_1 &= -R_0 \left( e^{-\frac{T_0}{R_1C_1}} + e^{-\frac{T_0}{R_2C_2}} \right) + R_1 \left( 1 - e^{-\frac{T_0}{R_1C_1}} \right) + R_2 \left( 1 - e^{-\frac{T_0}{R_2C_2}} \right) \\
d_2 &= R_0 e^{-\left(\frac{T_0}{R_1C_1} + \frac{T_0}{R_2C_2}\right)} - R_1 e^{-\frac{T_0}{R_2C_2}} \left( 1 - e^{-\frac{T_0}{R_1C_1}} \right) - R_2 e^{-\frac{T_0}{R_1C_1}} \left( 1 - e^{-\frac{T_0}{R_2C_2}} \right)
\end{align*}
\]

Note that the CT parameters are more complex functions of circuit parameters.
only, while the discrete parameters are functions of both circuit parameters and $T_s$, as indicated in (3.3) and (3.10).

### 3.4 Simulation results

#### 3.4.1 Simulation setup

Simulations are set up in MATLAB to compare the performance of CT and DT identification methods. In the simulation, the circuit of interest is assumed to have $R_0 = 1$ mΩ, $R_1 = 0.3$ mΩ, $R_2 = 0.6$ mΩ, $\tau_1 = 30$ s and $\tau_2 = 1000$ s, and the capacity of the battery is 40 Ah. It needs to be noticed that the simulated system is a typical stiff system, because it includes a fast and a slow time-constants.

The input excitation is shown in Figure 3.6c. It consists of five pairs of discharge and charge pulses, each lasting for 20 s. The amplitude of the pulse pairs are 0.5C, 1.0C, 1.5C, 2.0C and 2.5C, respectively. The rest periods after each discharge pulses are 40 s, and the rest periods after each charge pulses are 60 s. After the five pair of pulses, a 0.5C 2% SoC discharge is applied, followed by a 1-hour rest.

Various sampling intervals are used in the simulation, which are set to be 1 s, 0.1 s, and 0.01 s, respectively. White Gaussian noises with different signal to noise ratios (SNR) are added to the voltage output in the simulation to emulate the measurement noise of the system, such that

$$ v(k) = v_{det}(k) + n(k) \quad (3.31) $$

where $v_{det}$ is the deterministic (or noise-free) voltage signal, $n(k)$ is the measurement noise added to the noise-free voltage signal, and $v(k)$ is the noisy voltage measurement.

The SNR is defined as

$$ \text{SNR}_{\text{dB}} = 10 \log_{10} \frac{\sigma_{v_{det}}^2}{\sigma_n^2} \quad (3.32) $$

where $\sigma_{v_{det}}^2$ is the variance of $v_{det}$ and $\sigma_n^2$ is the variance of the added noises. The standard deviation of noises are chosen to be 0.01 mV, 1 mV and 10 mV respectively. Therefore the corresponding SNR values are 62 dB, 22 dB and 2 dB, respectively.
The SVF cut-off frequency is 0.01 rad/s. Unless otherwise specified, the intermediate data storage for all the simulation is 16 bits, and the prescaling technique introduced in Sec. 2.5 is applied to all simulation.

Monte Carlo simulations are used to evaluate the performance of the model identification methods, such that 100 different noise realizations are generated for each of the sampling intervals and noise levels. The Bode plots of the identified systems are presented for different methods in various conditions. Except DT LS, CT LSSVF and CT IVSVF methods, it is also interesting to see the performance of DT LS method with the same pre-filtering as in the CT methods, as suggested by [63]. The Bode plots of estimated models based on DT methods are presented in Figure 3.4, and those based on CT methods are presented in Figure 3.5.

3.4.2 Discussion of simulation results

Figure 3.4a and Figure 3.4b give the Bode plots for the CT models identified by the indirect DT LS-based method. The identified models are clearly biased at the low frequency ends. As the noise level or sampling rate increases, the identified systems are more biased.

The Bode plots for the systems identified by the DT LS methods with both input and output filtering are given in Figure 3.4c and Fig. 3.4d. The filter applied is the same as $L_2(s)$ with same cut-off frequency as SVF. It is hard to conclude solely

(a) DT LS method for different SNR ($T_s=0.1$ s, 16 bits). (b) DT LS method for different $T_s$ (SNR=22dB, 16 bits).
Figure 3.4: Monte Carlo simulation with different SNR and $T_s$. Bode plots of CT models from indirect DT methods.

From the two plots whether the pre-filtering improves the system identification, but at least the pre-filtering does not provide the desired system identification. Later simulation with 64 bit storage resolution in Figure 3.4e and Figure 3.4f demonstrates the effectiveness of the pre-filtering in high storage resolutions. The difference in the identification performance indicates that the pre-filtering is largely influenced by the rounding errors in DT identification.

Figure 3.5a and Figure 3.5b present the identification results of CT LSSVF method in various conditions. The performance of system identification is remark-
ably improved, which is due to the application of data pre-filtering and avoidance of discretization.

At last, Figure 3.5c and Figure 3.5d show that CT IVSVF identification has accurate identifications in all situations, where the Bode plots of the identified systems overlap that of the true system with a high fidelity except when the SNR is equal to 2dB when a bias can be observed in the low-frequency part of the response.

In summary, most of the indirect DT identification methods lead to large discrepancies in system identification, especially in the presence of noises and small
Table 3.1: Specification of battery under test.

<table>
<thead>
<tr>
<th>Material</th>
<th>Lithium ion polymer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Charge/discharge capacity</td>
<td>40.83/40.61 Ah</td>
</tr>
<tr>
<td>Nominal voltage</td>
<td>3.7 V</td>
</tr>
<tr>
<td>Maximum charge voltage</td>
<td>4.2 V</td>
</tr>
<tr>
<td>Minimum discharge voltage</td>
<td>2.7 V</td>
</tr>
</tbody>
</table>

3.5 Experimental results

3.5.1 Battery tests

In order to identify the parameters of a Lithium ion polymer cell, battery characterization experiments are conducted at room temperature (22°C-25°C). The specification of the battery under tests is given in Table 3.1. The procedure of the characterization tests is shown in Fig. 3.6a. The sampling rate in all the experiments is 1 Hz.

The capacity test consists of three charge/discharge cycles. In each cycle, the battery is charged with a constant current of 0.5C until the terminal voltage reaches the maximum charge voltage. Then the voltage is kept at the maximum charge voltage until the charge current is below 1/20C. After that, the battery is discharged at 0.5C until the minimum discharge voltage is reached. A 1-hr rest is applied after each charge/discharge operation. The charge/discharge capacity are calculated as the average value of the three cycles.

The charge/discharge OCV-SoC curves are obtained at 10% SoC step with 0.5C charge/discharge rate and 5-hr rest, as shown in Fig. 3.6b. It can be observed that the charge OCV curve is higher than the discharge curve due to the hysteresis effect. The maximum difference between charge/discharge curves is 22.6 mV. The
(a) Battery characterization procedure.

(b) OCV of the battery under test.

(c) HPPC test profile.

(d) HPPC pulses at SoC=50%.

Figure 3.6: Battery characterization and validation experiments.

average value of charge/discharge OCV curves is used in the model calculation for simplicity.

The HPPC test profile is the same as mentioned in Sec. 3.4.1. The HPPC test is repeated between 10% and 90% SoC with 2% SoC step. The current input and voltage output of the HPPC pulses at SoC=50% are shown in Fig. 3.6d.

Finally, Urban Dynamometer Driving Schedule (UDDS) cycles with 10 minutes rest periods are applied consecutively to the battery cell to validate the identified model. The initial SoC for UDDS test is 90%, and the test is terminated after the first cycle when SoC drops below 20%. The current profile of UDDS is scaled such that the maximum discharge current is 100 A.
3.5.2 Discussion of experimental results

In order to demonstrate the advantages of CT system identification, the performances of CT LSSVF and CT IVSVF estimators are compared with DT LS method and DT LS with pre-filtering. The cut-off frequency for both of the filters are 0.025 rad/s and the storage resolution is 16 bits.

The voltage outputs of the simulated models and experiments in UDDS are plotted in Fig. 3.7a, and the zoomed-in range between 5,900 s and 7,400 s are shown in Fig. 3.7b.

The results show that

i) The indirect DT methods have the larger overall error.

ii) The DT LS method with pre-filtering has similar noise levels to the CT LSSVF method in some of the cycles, however, the systems identified are clearly biased in the 5th, 6th and 9th cycle. The defect in robustness is mainly caused by its high sensitivity to unmodeled dynamics and colored noises in the experiment.

iii) The two direct CT identification methods have better performance over other methods. Furthermore, CT IVSVF estimator gives better estimation because

(a) Voltage values and errors across all UDDS tests.
the newly introduced instrumental variable is less correlated to equation error.

Based on the findings in simulation results, the DT LS method tends to estimate the poles of the system to be larger, then the corresponding time-constants are smaller. This can be observed in Fig. 3.8 as well, where the time-constant estimates of DT LS are the smallest among all the methods.

It needs to notice that DT LS presents acceptable results in experiments because the UDDS cycle mainly consists of high frequency contents, where it gives reasonable identification in the simulation as well. However, it has large bias in larger time-constant estimates, which will lead to larger discrepancies when the input is constant. This can be visualized by its larger discrepancies at beginning of rest periods between UDDS cycles.

The mean absolute error (MAE) and root mean squares error (RMSE) of the aforementioned estimators within the whole experimental period are listed as in Table 3.2. It validates that the CT identification methods have better overall performance and CT IVSVF method gives voltage estimations with the smallest error.
Figure 3.8: Time-constant estimates from experimental data with different methods.

Table 3.2: MAE and RMSE of model voltage estimation in whole UDDS validation.

<table>
<thead>
<tr>
<th>Method</th>
<th>DT LS</th>
<th>DT LS filter</th>
<th>CT LSSVF</th>
<th>CT IVSVF</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAE (mV)</td>
<td>8.59</td>
<td>8.71</td>
<td>6.34</td>
<td>4.27</td>
</tr>
<tr>
<td>RMSE (mV)</td>
<td>9.35</td>
<td>10.36</td>
<td>6.96</td>
<td>4.95</td>
</tr>
</tbody>
</table>

3.6 Performance of model-based fault diagnosis

The model identified in the previous sections can serve as the analytical redundancy for fault diagnosis purposes. The basic principle is to use the online measured current as the model input, and then compare the model voltage output with the real measurement. If the model has been well established and validated in normal working conditions, a large residue will indicate an unmodeled situation, or the fault condition.

An ESC experiment with short duration is induced to illustrate the working principle of the model-based fault diagnosis method. The same battery cell, as introduced in Table 3.1, is used, and it is externally shorted with a copper wire to induce the fault.

After the voltage and current data are collected, a model-based fault diagnosis algorithm is run to simulate its online performance. The current data are read and the
voltage values are calculated. The experiment data and simulation data are provided in Figure 3.9.

**Figure 3.9:** Performance of model-based fault diagnosis method.

Figure 3.9 shows that the sudden external short does not ruin the battery operation, but leaves a negligible voltage drop, which is too small to be identified by the pure voltage threshold-based detection method. However, when the output from the simulation model is compared with the real output, a large residue can be easily identified at 1117 s. Given the typical MAE and RMSE in Table 3.2, a 50 mV threshold value is set as the threshold to distinguish between fault and not-fault states.

Clearly, the more accurate the identified model is, the more confident the algorithm is with the diagnosis decisions. Thus the CT system identification methods are more desired for battery fault diagnosis applications.
3.7 Summary

This chapter presents the advantages of CT system identification methods in battery ECM parameter estimation. The combination of fast dynamics induced by charge transfer and slow dynamics from diffusion cause the dynamics of a battery to exhibit stiff system behavior. CT identification reduces the sensitivity of the model parametrization in case of a stiff dynamic system, leading to improvements on battery parameter estimation, and thus fault detection performances.

The general modeling of both CT and DT $n^{th}$-order ECM is first discussed. Then it is shown that the $n^{th}$-order ECM is identifiable if the order of the time-constants is strictly defined. The comparison between CT and DT methods indicates that DT identification methods are less robust due to undesired sensitivity issues in transformation of discrete domain parameters. In CT parameter identification, SVF is used to smoothen the time-derivative terms. After that, the IV method is applied to further increase the estimation accuracy by reducing the correlation between equation error and regressor.

Simulation results show that the CT identification methods demonstrate higher accuracy in stiff system estimations given different sampling intervals and noise levels, because of the inherent SVF pre-filtering and the avoidance of pole discretization. Characterization experiments are conducted and different identification methods are used to identify the battery parameters, including DT LS, DT LS with pre-filtering, CT LSSVF and CT IVSVF. The results indicate that the CT identification methods result in the smallest mean absolute error and root mean square error. Among all, the best output voltage prediction is obtained by CT IVSVF method.

The model obtained in this chapter is applied in the fault diagnosis of ISCs, and the performance is compared with that of the threshold-based method. The results show that the model-based method can identify the fault when all the measurements are within safe limit, and the threshold-based method fails to identify the fault.

The disadvantages of the model-based fault identification method are

i) The fault detection is ambiguous, because the detection algorithm cannot tell whether the fault comes from a true fault or an inaccurate model.

ii) When a sensor fault occurs, the model-based detection method flags fault pos-
itive fault.

iii) The model-based fault detection cannot deal with cell inconsistencies, unless every single cell is modeled and tracked along its service life, which is not practical.

iv) The computational cost of the model-based method is high compared with the simple threshold-based method.

This chapter is based on the following published paper,

Chapter 4

The correlation-based fault detection method

4.1 Introduction

When a closer insight is given to the redundancy-based fault diagnosis methods, it can be found that they are designed for single systems, or the target system is unique and can function individually without any duplicative parts. This is the reason why it requires either a hardware or analytical redundancy to provide a second output to compare with.

Keep this in mind, it is worth noting that there is a fundamental difference in the battery system. A battery pack includes multiple same battery cells connecting in series, meaning that the cells share the same current. In other words, a battery system consists of multiple same systems with same inputs, and thus the voltage outputs should be similar, if not at fault conditions. In this way, one cell output can be compared with that of any other cells, or all the other cells can serve as the hardware redundancies of one single cell, even though there is physically no redundancy in the system. It is important to notice that the comparison among cells is robust because the outputs come from real systems, which are guaranteed to be accurate and does not suffer from any convergence issues.

Rigorously speaking, the battery cells within a battery pack are not exactly the same. There are variations in the manufacturing process, thermal conditions in
usage, balance state, etc [64, 65]. In general, all these variations are reflected into two essential states, i.e., SoC and SoH. These two states affect the static and dynamic behavior of a battery cell by different OCV and internal resistance, respectively. The different OCV leads to an offset in the cell voltages and the difference in internal resistance causes voltage fluctuations with different amplitudes. If the voltage outputs of the battery cells are simply compared, these voltage differences can easily exceed the preset threshold value, making this simple comparison not robust in real applications.

Figure 4.1: Correlation coefficient is the solution to coping with cell inconsistencies.

In order to avoid the influence of inconsistencies in the battery pack upon fault detection, this chapter introduces a correlation-based method for short circuit detection in lithium ion battery packs. The main idea is illustrated in Figure 4.1, in which the key is to capture the unusual voltage variation at the initial phase of a short circuit fault by calculating the correlation coefficients of the cell voltages. Since the correlation coefficient is independent of the mean value and the amplitude of the fluctuations, when applying to the cell voltages, it eliminates the inconsistencies
in OCV and internal resistance, hence does not lead to false positive faults when the batteries are in different SoC or SoH. Moreover, this method is self-redundancy-based, because the correlation coefficient calculation only involves voltage outputs from different cells, thereby saving the extensive effort in modeling and testing.

Based on these desired features, an online short circuit detection algorithm is developed. A moving window filter is utilized to forget past data and maintain the detection sensitivity to faults. An additive square wave is designed to prevent false detections when the noises dominate the voltage variations during rest periods. Simulations are used to illustrate the functions of the moving window and the square wave in different scenarios. Experiments are conducted to validate the feasibility of the method, and to demonstrate the fault isolation. Finally, the key assumptions of the proposed method are discussed and the root causes of different detection results from different methods are analyzed.

4.2 Method description

4.2.1 Correlation coefficient

In statistics, correlation coefficient, or Pearson product-moment correlation coefficient, is a degree of measurement indicating the linear relation between two variables [66]. It is expressed as

$$r_{X,Y} = \frac{\text{cov}_{X,Y}}{\sigma_X \sigma_Y} = \frac{\sum_{i=1}^{n}(x_i - \mu_X)(y_i - \mu_Y)}{\sqrt{\sum_{i=1}^{n}(x_i - \mu_X)^2} \sqrt{\sum_{i=1}^{n}(y_i - \mu_Y)^2}}$$

(4.1)

where $r_{X,Y}$ is the correlation coefficient of variables $X$ and $Y$, $\text{cov}_{X,Y}$ is the covariance of $X$ and $Y$, $\sigma_Z$ is the variance of variable $Z$, $\mu_Z$ is the mean value of variable $Z$, and $n$ is the number of samples in the data. The correlation coefficient is unitless, and ranges from +1 to -1 inclusive, where +1 indicates total positive correlation, 0 indicates no correlation and -1 indicates total negative correlation.

An important property of the correlation coefficient is given as

$$r_{\alpha X + \beta Y} = r_{X,Y}$$

(4.2)
where $\alpha$ and $\beta$ are two constants. This property is intuitive because when an offset $\beta$ is added to any of the variables, it is subtracted from the mean values in (4.1), and when the fluctuation amplitude of a variable is multiplied by $\alpha$, it multiplies both the numerator and denominator by $\alpha$. Hence, the correlation coefficient measures whether the trend of two curves matches, instead of their exact shape.

This feature is indeed an ideal property in coping with the inconsistencies in lithium ion batteries when: 1) the imbalanced batteries demonstrate different OCV, and 2) the cells in different aging levels exhibit different internal resistances. If the correlation coefficient of two cell voltages is calculated, the difference in OCV is removed because the static offset does not influence the correlation coefficient, and the difference in internal resistances is eliminated because the correlation coefficient is also independent of the fluctuation amplitudes. Therefore, ideally, the correlation coefficient of two series cell voltages should be close to +1 during normal operations. When a short circuit occurs, the abnormal voltage drop influences the synchronized fluctuation on battery voltages, thus being reflected by the reduced correlation coefficient.

### 4.3 Extension to real application

#### 4.3.1 Recursive estimation

For online implementation, the correlation coefficient should be calculated recursively. Equation (4.1) is not a satisfactory formula for such application. Although the mean values can be updated after every sampling recursively, the subtractions from mean values have to be calculated individually.

An equivalent expression of the correlation coefficient can be obtained by multiplying both the numerator and denominator of (4.1) by $n$, as

$$r_{X,Y} = \frac{n \sum_{i=1}^{n} x_i y_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i}{\sqrt{n \sum_{i=1}^{n} x_i^2 - (\sum_{i=1}^{n} x_i)^2} \sqrt{n \sum_{i=1}^{n} y_i^2 - (\sum_{i=1}^{n} y_i)^2}}$$  

Equation (4.3) does not require subtractions from the mean values, so it is more appropriate for recursive estimation. The formula of the recursive estimation is
then obtained as

\[ P_k = P_{k-1} + x_i y_i \]
\[ Q_k = Q_{k-1} + x_i \]
\[ R_k = R_{k-1} + y_i \]
\[ S_k = S_{k-1} + x_i^2 \]
\[ T_k = T_{k-1} + y_i^2 \]

\[(r_{X,Y})_k = \frac{kP_k - Q_k R_k}{\sqrt{kS_k - Q_k^2 \sqrt{kT_k - R_k^2}}}\] \hspace{1cm} (4.4)

### 4.3.2 Forgetting mechanism

Equation (4.3) can be used to obtain the similarity of the time domain trends for two voltage curves from the beginning of measurement. However, there are still several difficulties in implementation: 1) if the fault occurs long time after the beginning of measurement, the abnormal behavior will have negligible effect on the correlation coefficient due to the high similarity of the long history data; 2) as time goes by, the magnitudes of updated quantities in (4.4) become larger and larger, and will eventually exceed the storage limits of the onboard microprocessors. The most straightforward approach to solving the abovementioned problems is to employ a moving window filter for data processing, i.e., at each time instant, the correlation coefficient for the data only in a history time window is calculated. Then (4.4) is modified as

\[ P_k = P_{k-1} + x_i y_i - x_{i-w} y_{i-w} \]
\[ Q_k = Q_{k-1} + x_i - x_{i-w} \]
\[ R_k = R_{k-1} + y_i - y_{i-w} \]
\[ S_k = S_{k-1} + x_i^2 - x_{i-w}^2 \]
\[ T_k = T_{k-1} + y_i^2 - y_{i-w}^2 \]

\[(r_{X,Y})_k = \frac{wP_k - Q_k R_k}{\sqrt{wS_k - Q_k^2 \sqrt{wT_k - R_k^2}}}\] \hspace{1cm} (4.5)

where \( w \) is the size of the moving window. It needs to be noted that (4.5) should be initialized by (4.4) in the first \( w \) samples.
It is also worth noticing that the window size should be chosen with special care. If a large set of data is employed in the calculation, the abnormal voltage variation led by short circuit will have negligible effects in the correlation coefficient. Hence, in order to keep the detection sensitivity to faults, a moving window with a small size is preferred. On the other hand, when the moving window size is too small, the noise will be regarded as abnormal fluctuations and the measurement noises will influence the calculation as well. Therefore, a proper size of moving window should be selected based on the application.

4.3.3 Special case when noises dominate

When two signals are added to $X$ and $Y$, respectively, equation (4.1) can be derived as

$$r_{X+N,Y+M} = \frac{\text{COV}_{X+N,Y+M}}{\sigma_{X+N}\sigma_{Y+M}} = \frac{\sum_{i=1}^{n} (x_i - \mu_X + N_i - \mu_N)(y_i - \mu_Y + M_i - \mu_M)}{\sqrt{\sum_{i=1}^{n} (x_i - \mu_X + N_i - \mu_N)^2} \sqrt{\sum_{i=1}^{n} (y_i - \mu_Y + M_i - \mu_M)^2}}$$

(4.6)

where $N$ is the signal added to $X$ and $M$ is the signal added to $Y$. Assume that both $N$ and $M$ are independent of $X$ and $Y$. Equation (4.6) can be simplified as

$$r_{X+N,Y+M} = \frac{\sum_{i=1}^{n} (x_i - \mu_X)(y_i - \mu_Y) + \sum_{i=1}^{n} (N_i - \mu_N)(M_i - \mu_M)}{\sqrt{\sum_{i=1}^{n} (x_i - \mu_X)^2 + \sum_{i=1}^{n} (N_i - \mu_N)^2} \sqrt{\sum_{i=1}^{n} (y_i - \mu_Y)^2 + \sum_{i=1}^{n} (M_i - \mu_M)^2}}$$

(4.7)

There are two terms in the numerator of (4.7). When the batteries are at rest, the first term is zero because the voltages are very close to their OCVs. When $N$ and $M$ are independent and identically distributed white noises, the second term is zero as well. This indicates that the correlation coefficient is close to zero in this situation. This small value will lead to a sudden drop in the calculation and surely triggers a false positive fault, which is not desired.

If (4.7) is further expanded to three signals and preferably the mean values of
the added signals are all zero, the correlation coefficient can be expressed as

\[
\begin{align*}
    r_{X+A+N,Y+B+M} &= \\
    &\frac{\sum_{i=1}^{n}(x_i - \mu_X)(y_i - \mu_Y) + \sum_{i=1}^{n} A_i B_i + \sum_{i=1}^{n} N_i M_i}{\sqrt{\sum_{i=1}^{n}(x_i - \mu_X)^2 + \sum_{i=1}^{n} A_i^2 + \sum_{i=1}^{n} N_i^2}} \\
    &\sqrt{\sum_{i=1}^{n}(y_i - \mu_Y)^2 + \sum_{i=1}^{n} B_i^2 + \sum_{i=1}^{n} M_i^2}
\end{align*}
\]

(4.8)

where \( A \) and \( B \) are the newly added signals to \( X \) and \( Y \), and assume they are independent of \( X, Y, N \) and \( M \). A solution to avoiding the zero correlation coefficient is provided in (4.8) when \( A \) and \( B \) are dependent. In such cases, when the batteries are at rest, equation (4.8) is simplified as

\[
\begin{align*}
    r_{X+A+N,Y+B+M} &= \frac{\text{COV}_{A,B}}{\sqrt{\sigma^2_A + \sigma^2_N \sqrt{\sigma^2_B + \sigma^2_M}}} \\
    &\approx r_{A,B}, \sigma^2_N \ll \sigma^2_A, \sigma^2_M \ll \sigma^2_B
\end{align*}
\]

(4.9)

If the variance of noises are negligible to the variance of \( A \) and \( B \), the correlation coefficient of \( X + A + N \) and \( Y + B + M \) will be the same as that of \( A \) and \( B \).

Taking advantage of this feature, a same signal can be added to both voltage measurements, which means \( r_{A,B} \) is 1. The added signals should be negligible when there are persistent inputs, meanwhile, the variance of the two signals should be larger than that of the noises, such that the correlation coefficient of the two voltages will be close to 1 when the batteries are at rest.

A simple design is to add a square wave with the amplitude of 3 times the standard deviation of the noise standard deviation, namely, 9 times the variance of the noise, as illustrated in

\[
\begin{align*}
    r_{V_1+SW+N,V_2+SW+M} &= \frac{\text{COV}_{SW,SW}}{\sqrt{\sigma^2_{SW} + \sigma^2_N \sqrt{\sigma^2_{SW} + \sigma^2_M}}} \\
    &= \frac{9\sigma^2_N}{10\sigma^2_N} = 0.9
\end{align*}
\]

(4.10)

where \( SW \) is the additive square wave. As a result, the correlation coefficient is close to 0.9 when the batteries are at rest. Clearly, when the amplitude of the square wave is larger, the correlation coefficient is closer to 1 when the battery is at rest. However, the increase in amplitude also decreases the detection sensitivity to the actual voltage drop. In the design of the additive square wave, 0.9 is a reasonable objective when the threshold is set to be 0.5.

The period of the square wave should be smaller than the window size. A trivial selection of period can be 2 samples.
4.3.4 Fault isolation

In real applications, tens or hundreds of cells are connected in series. Here we assume only the minority of the cells may have short circuit fault at the same time. Otherwise, the short circuit fault can be easily detected by module or pack level voltage monitoring.

In order to acquire the status of each battery cell, the correlation coefficients for every pair of neighboring cells need to be calculated, including that for the first and last cell, as illustrated in Figure 4.2. When a fault occurs on one of the cells, the two related correlation coefficients drop and the fault location can be isolated by the overlapped index number. For example, when both $r_{V_1,V_2}$ and $r_{V_2,V_3}$ demonstrate a sudden drop, it indicates a fault on $V_2$ because it is not in the same trend as those of $V_1$ and $V_3$. The same strategy can be applied when multiple faults occurs, as long as the fault cells are the minority of the whole pack.

![Figure 4.2: Correlation coefficient calculation for every pair of neighboring cells.](image)
4.4 Simulation

4.4.1 Simulation setup

The fault conditions are simulated to demonstrate the feasibility of the proposed detection method. First, an experiment is conducted to apply the UDDS to two battery cells connecting in series. The specification of the batteries under test is the same as that in Table 2.2, and the voltage responses of the two cells, $V_1$ and $V_2$ are given in Figure 4.3. The sampling time in the experiment is 0.1 s.

![Figure 4.3](image.png)

**Figure 4.3:** Voltage responses of two batteries cells used in simulation (without fault signal).

Then, a fault signal is constructed by reducing one voltage sample by 100 mV to simulate the sudden voltage drop recovery at the initial phase of ISC. The fault signal is added to $V_1$ and denote the synthesized data as $V_{1f}$. In order to demonstrate the basic working principle of the detection algorithm, the correlation coefficient of $V_1$ and $V_{1f}$ are first calculated. It needs to be noted that, except the fault signal added, the two voltage responses are exactly the same, including the measurement noises. The two voltages are plotted in Figure 4.4, with the added fault highlighted with an ellipse. The corresponding correlation coefficient of the two voltages are provided in
Figure 4.5 with inset of detection at fault. The moving window sizes are 30, 40 and 50 samples.

Figure 4.4: Voltage responses with fault signal added.

Figure 4.5: Detection results with inset at faults.
After that, independent white noises with the same standard deviation of 1 mV are added to $V_1$ and $V_{1f}$, respectively, to emulate the noisy measurements. The noisy voltages, $V_{1,n}$ and $V_{1f,n}$ are given in Figure 4.6a, and the correlation coefficient of them is calculated in Figure 4.6b.

Later, the square wave discussed in Sec. 4.3.3 is added to $V_{1,n}$ and $V_{1f,n}$, denoting as $V_{1,n,s}$ and $V_{1f,n,s}$, and the corresponding correlation coefficient is plotted in Figure 4.6c. The mean value of the square wave is zero, the amplitude is 3 mV and the period is 2 samples.

![Figure 4.6: The drop in $r$ when batteries are at rest is greatly reduced with added square wave.](image)

Finally, real fault detections are simulated by calculating the correlation coefficient of $V_{1f,s}$ and $V_{2,s}$. In this simulation, the window size is 30 samples, and the duration of the voltage drop, denoted as $d$, are varied to be 1, 5, 10, 30, 40 and 50 samples, as shown in Figure 4.7 and Figure 4.8. A threshold of 0.5 is marked as dashed black lines and is selected to trigger the fault detection.
It can be learnt from Figure 4.3 that the internal resistances of the two batteries under test are different. Given the same current input, the voltage difference between

4.4.2 Discussion of simulation results

It can be learnt from Figure 4.3 that the internal resistances of the two batteries under test are different. Given the same current input, the voltage difference between
the two cells can be larger than 100 mV at around 150 s. This large difference will trigger false positive faults if the voltage difference threshold method is applied, or if only one model is tracked online in the model-based detection method. Figure 4.4 shows that the fault signal is added to $V_1$ at around 700 s. The voltage value at fault is not out of the voltage operation range given in Table 2.2, and thus cannot be detected by the voltage threshold method.

The correlation coefficient calculated in Figure 4.5 manages to capture the off-trend voltage drop recovery, and the fault is flagged by the drop in the correlation coefficients. The comparisons among the calculation with three different window sizes indicate that a smaller window size leads to higher sensitivity to abnormal voltage variations. Meanwhile, when independent white noises are added to the voltage measurements, the correlation coefficient provided in Figure 4.6b exhibits more fluctuations than that in Figure 4.5. It needs to be noted that as the size of the moving window increases, part of the fluctuations is smaller, as the ones at around 160 s, owing to the reduced sensitivity to noises.

However, part of the fluctuations remains the same in spite of the variation in window sizes, as the ones at around 100 s. If a closer look is given to the voltages in Figure 4.6a, it can be found that whenever there is a voltage plateau in measurements, there is an unrecoverable fluctuation in the correlation coefficient. Actually, this phenomenon has been well-explained by Sec. 4.3.3 that when the batteries are at rest, the correlation coefficient will drop as indicated in (4.7). The proposed solution is to add a square wave to the voltage measurements with an amplitude of 3 mV and a period of 2 samples. Figure 4.6c presents the correlation coefficient with the square wave added, indicating that the induced fault can be easily identified.

In the simulation, the induced fault is detected with the proposed correlation-based method, whereas the other detection methods lead to various issues. The detection results are summarized in Table 4.1.

It is understood that the correlation coefficient measures the similarity of the two signals. It can be inferred when the voltage drop led by faults lasts longer within the moving window, the similarity of the two voltage measurements degrades further, and thus the drop in the correlation coefficient will be larger, as illustrated in Figure 4.7. This ensures the robustness of this detection method when multiple samples in
Table 4.1: Comparison of the simulated short circuit detection results.

<table>
<thead>
<tr>
<th>Detection method</th>
<th>True fault</th>
<th>False fault</th>
</tr>
</thead>
<tbody>
<tr>
<td>Voltage-threshold-based</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Voltage-difference-threshold-based</td>
<td>✔</td>
<td>✔</td>
</tr>
<tr>
<td>Model-based</td>
<td>✔</td>
<td>✔</td>
</tr>
<tr>
<td>Correlation-based</td>
<td>✔</td>
<td></td>
</tr>
</tbody>
</table>

The simulated fault voltages $V_{1f}$ with different lengths are demonstrated in Figure 4.9. The different faults start at the same time, but recover at different time instants. It can be observed that when the voltage drop lasts longer than the length of the moving window, the batch-wise voltage data within the moving window are the same at the initial stage of the short circuits, as the cases of 30, 40 and 50 samples. Hence, in these cases, the variations in the correlation coefficients are the same at the initial stages, regardless of the length of the voltage drop, as shown in Figure 4.8. Therefore, the fault detection times for short circuits with long durations are the same, as summarized in Table 4.2. This property makes the proposed method applicable to ESC detection as well, where the voltage drop may be longer than the moving time window.

Table 4.2: Fault detection times of correlation-based method for different short circuit durations.

<table>
<thead>
<tr>
<th>Fault duration (sample)</th>
<th>1</th>
<th>5</th>
<th>10</th>
<th>30</th>
<th>40</th>
<th>50</th>
</tr>
</thead>
<tbody>
<tr>
<td>Detection time (sec)</td>
<td>1.1</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
</tr>
</tbody>
</table>
4.5 Experiment

4.5.1 Experiment setup

An experiment is set up to validate the proposed fault detection approach. The schematics for experimental setup is shown in Figure 4.10. Four battery cells, same as those introduced in Table 2.2, are connected in series. A customized BMS is equipped to monitor the voltage, current and temperature of the battery string. All the data are collected with dSPACE Micro-Autobox and saved through ControlDesk in the host computer. The charge/discharge commands are executed by the direct current power source and electronic load connecting in parallel with the battery string. The hardware implementation is provided in Figure 4.11.

The battery string is then applied with a UDDS cycle in the room temperature. At 42.4 s of the UDDS cycle, a jump wire with 0.36 Ω resistance is used to short the positive and negative terminal of cell #4 for 1.3 s. The corresponding voltage responses for the four cells are given in Figure 4.12, and the temperature responses are given in Figure 4.13. The sampling interval in the experiment is 0.1 s.
Figure 4.10: Schematics for validation experiment setup.

Figure 4.11: Hardware setup for validation experiment setup.
**Figure 4.12:** Cell voltages in the validation experiment.

**Figure 4.13:** Cell temperatures in the validation experiment.
4.5.2 Discussion of experiment results

It can be observed from Figure 4.12 that when cell #4 is shorted by the jump wire, the voltage suddenly drops to approximate 2.6 V, and the voltage recovers after the short is removed. The voltage drop does not touch the discharge voltage limit given in Table 2.2. From the temperature plot in Figure 4.13, the temperature response of cell #4 does have a higher rise than other cells after the fault occurrence, however, the amount is only 0.3 °C, which is negligible to notice in real applications. Since the short circuit current does not pass the current sensor on the BMS board, the short circuit is unobservable from current measurements. Thus the voltage, current or temperature threshold-based detection methods do not flag any fault in the scenario.

It is also worth noting that the SoCs of the four batteries under test are different. The OCV of cell #2 is lower than the average OCV of the other three cells by 22 mV. This difference may lead to false detection if the voltage difference threshold method is applied. When the model-based method is applied to track the voltage of only one of the cells, it will also result in a false fault detection.

The correlation coefficients for the neighboring cells are calculated and plotted in Figure 4.14. The size of the moving window is 30 samples. The amplitude of the square wave added is 3 mV and the period is 2 samples. The correlation coefficients for the first two neighboring cell pairs are close to 1 in the experiment, indicating these three cells follow the same variation in the whole process. Whereas, the correlation coefficient of cell #3 and cell #4 drops abruptly when the fault occurs because of the off-trend voltage drop. The location of the fault can be determined as cell #4 because the same drop is captured in both $r_{(3,4)}$ and $r_{(4,1)}$.

A threshold value of 0.5 is marked in Figure 4.14 to flag the short circuit fault. The voltage drop is captured in the voltage reading at 42.5 s, and the correlation coefficient flags the fault at 42.5 s. It is because the voltage variation is much larger than the normal voltage fluctuations, leading to a large drop in the correlation coefficient once the voltage drop is captured. This demonstrates the prompt response of the proposed fault detection method in real applications.
Figure 4.14: Correlation coefficients calculated for the neighboring cells.

4.6 Further discussion

4.6.1 Key assumptions

The proposed fault detection method utilizes the measurement of similarity from the correlation coefficient, and determines a fault when the similarity is low. This section discusses the key assumptions which may be violated in real applications and the corresponding mitigation methods.

4.6.2 White noises

In the derivation in Sec. 4.3.3, the noises in the measurement are assumed to be white noises, which is not true in real applications. Except that, given a small number of samples, the noises can hardly exhibit its statistical property under the law of large numbers [38]. As a result, the variance of the noises may be higher, and this can be compensated by adding a square wave with higher amplitudes.
4.6.3 Synchronized measurement

The voltages in a vehicular battery pack are usually measured sequentially to save hardware cost. For the experiment in this manuscript, the voltages are sequentially updated, but they are shifted to align with one another in the time domain before the correlation coefficient calculation. Otherwise, one voltage always leads or lags others, leading to false detections. One solution is to shift the measurements in the moving window, and calculate the correlation coefficient afterwards, as done in this manuscript. The other solution is to utilize the cross-correlation which calculates the correlation coefficients of the time shifted version of two signals [67, 68]. The time difference in the cross-correlation calculation will be the sampling interval.

4.6.4 Minority at fault

It is discussed in Sec. 4.3.4 that the fault isolation is not accurate when the majority of the cells is in fault at the same time. In the extreme condition, when the whole pack is in the ESC condition, the correlation coefficients are close to 1, because the voltage trends are the same. However, when multiple ESCs occur at the same time, the faults can be easily detected by module or pack level voltage monitoring. In addition, the ISCs do not occur simultaneously in real applications.

4.6.5 Calculation of mixed-voltage correlation

Instead of calculating the correlation coefficients of individual voltage measurements, it is also feasible to calculate those of the mixed voltages. For example, in the case of Fig. 4.14, $r_{V_1,V_2+V_3}$, $r_{V_2,V_3+V_4}$, $r_{V_3,V_4+V_1}$ and $r_{V_4,V_1+V_2}$ can be calculated to detect and isolate the fault.

Indeed, the value of $r_{V_1,V_2+V_3}$ is the same as that of $r_{V_1,\frac{1}{2}(V_2+V_3)}$. Thus, the mix of the cell voltages bring the benefit of noise reduction from the measurement channels. However, at the same time, it reduces the voltage variation at fault occurrence. Ideally, the best fault indicator should be the correlation of the fault cell with the average of all other cell voltages, which achieves both largest voltage variation and least noises.
4.6.6 Short with low resistances

The proposed method captures the abrupt voltage drop by calculating correlation coefficient within a moving window. A thorough study of ISCs with different resistances has been conducted in [33]. It shows that not every ISC has abrupt voltage drop, or low resistance short. With large short resistances, the voltage curves follow the same trend over the relatively short moving time windows and thus the fault cannot be identified. Nevertheless, the proposed method is still meaningful because the internal shorts with low resistances require immediate mitigation, and are more dangerous due to the instant excess heat generation. Indeed, the large resistance ISC can also be detected by the correlation-based method, when the moving window filter is modified as

\[ W_i = \begin{cases} 
1, & i = n - jk, j = 0, 1, \cdots, w - 1 \\
0, & \text{otherwise}
\end{cases} \] (4.11)

where \( W \) is the function of moving window filter, and \( k \) is the number that adjusts the time span of the moving window filter. This filter evenly samples \( w \) points within a time span of \( kw \). It needs to be noted that the moving average filter used in the previous sections is a special case of (4.11) with \( k = 1 \). When \( k \) is large, this filter can capture the voltage behavior over long periods of time, thereby identifying internal shorts with large resistances.

4.6.7 Comparison of different detection methods

Because of the high cost of hardware redundancy, the software redundancy is the most applied fault detection methods in battery systems. The voltage threshold method is the simplest model, which only considers the safe operation range of the system, and is ignorant of the input information. It is easy in implementation, but the weakness is that the out-of-range voltage is not a necessary condition for faults. In other words, a battery can still be faulty when the voltage is in the safe range.

An improvement can be made by taking the input into consideration, and then it gives rise to the model-based fault diagnostic methods. The methods are able to distinguish the fault conditions when the voltages are within the safe range, but the tradeoff is their substantial effort in maintaining the robustness and accuracy.
of the battery models in difference situations. Except that, there may be a false positive alarm when a fault is flagged, due to an inaccurate battery model or the inconsistencies among individual cells.

The proposed method directly compares the outputs of the multiple cells, and identifies the fault by the off-trend voltage behavior. The battery model is then not needed, which saves the effort in modeling, because every other cell can be the hardware redundancy of the current cell. It is interesting to note that the voltage difference threshold method is a special case of the proposed method, where it assumes all the cells are the same. This assumption is not true when the SoC and SoH of the cells varies, and is compensated well by the properties of correlation coefficients. A brief summary of the comparisons of different detection methods is provided in Table 4.3.

**Table 4.3:** Comparison of different detection methods.

<table>
<thead>
<tr>
<th>Detection method</th>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Voltage threshold</td>
<td>Easy implementation</td>
<td>False negative faults within the operation range</td>
</tr>
<tr>
<td>Model-based</td>
<td>Fault detection in the operation range</td>
<td>Substantial modeling work; ambiguity in fault detection</td>
</tr>
<tr>
<td>Voltage difference</td>
<td>No modeling work</td>
<td>False positive faults when SoCs or SoHs are not consistent</td>
</tr>
<tr>
<td>Correlation-based</td>
<td>No modeling work; fault detection with inconsistent SoCs or SoHs</td>
<td>Need to be combined with module/pack level monitoring</td>
</tr>
</tbody>
</table>

### 4.7 Summary

A correlation-based fault detection method is introduced in this chapter, which does not require hardware and analytical redundancy, thus saving the hardware cost and effort in system modeling. The concept of correlation coefficient is first intro-
duced. It is proved that the correlation coefficient can detect the initial stage of short circuits by capturing the off-trend voltage drop, and reflect the variation to the drop in correlation coefficient, in spite of the cell inconsistencies in SoC or SoH.

Next, the correlation coefficient is expressed in the recursive form for online application. A moving average window is applied to keep the most recent voltage trends of the cells, while maintaining the detection sensitivity to short circuit faults. A square wave is added to the voltage measurements to prevent the false detection when the batteries are at rest. In addition, it is analyzed that the short circuit fault can be isolated by identifying the overlapped cell in the dropped correlation coefficients.

Moreover, simulation and experiment results validate the analysis, and demonstrate the scenarios where the proposed method can robustly identify the faults, while the voltage threshold, voltage difference threshold and model-based method lead to either false negative faults or false positive faults.

At last, the key assumptions in the proposed method are discussed. It is explained that the proposed method can detect the short circuits with a large short resistance by modification of the moving window. The comparison with other detection methods shows that the proposed method does not require modeling work, and provides robust short circuit detection regardless of the inconsistencies within the battery pack.

This chapter is based on the following published paper,

Chapter 5

The interleaved voltage measurement method

5.1 Introduction

Today’s widely applied voltage measurement method uses individual voltage sensors, or measurement integrated circuits, to measure the voltage values of individual cells [69]. This one-to-one correspondence ensures that the voltage of every single cell is monitored. To measure the voltages of a series string of batteries, instead of using one voltage measurement circuit for each of the cells, switches are typically applied to reduce cost in measurement circuits and ADC [70, 71]. The switches are turned on with pairs, such that the cell voltages in a string is updated one at a time sequentially. When any voltage reading shows abnormal values, the battery system will be stopped for protection purposes and mitigation methods will be employed.

It needs to be pointed out that sensors have their own reliability. In other words, a voltage sensor in fault condition may lead to a false positive cell fault detection, however the mitigation methods for these two types of faults differ significantly. In the case of cell faults, some immediate, costly or even dangerous mitigation methods should be taken, including cutting the power from battery pack in the middle of drives and informing the fire department; while in the case of sensor faults, more moderate mitigation methods can be applied, such as switching the vehicle into limp home mode and pushing a request for battery pack maintenance. For any of the fault
diagnosis method introduced in the previous chapters, a sensor failure will surely induces a false positive fault and leads to improper fault mitigation. Thus, it is critical to distinguish between sensor faults and cell faults in order to apply proper mitigation and ensure reliable operation of EVs.

Abundant researches have been conducted to investigate the methods to detect and isolate sensor faults. Similar to the cell fault detection, the sensor fault detection is mostly redundancy-based. The most widely applied method is hardware redundancy, where measurements of the same signal are given by multiple sensors [72]. Clearly, this sensor fault detection feature is equipped at the cost of additional hardware expense and more complex system which may be more prone to failure. Analytical redundancy is then proposed as opposed to hardware redundancy, which utilizes the output from mathematical models of the system and compare the output with sensor measurements [73]. This method does not require additional hardware, however, it is complex to maintain the robustness of the model given uncertainties, disturbances and various failure modes of the system. Indeed, the analytical sensor failure detection is the same as that of the cell failure detection in system modeling, and the only difference lies in which information is trusted when the two piece of information is not consistent, the sensor reading or the cell status. If an abnormal sensor reading is trusted, a cell fault is determined. Or if the cell status is trusted to be safe, then a sensor failure is determined.

Given the inherent disadvantages of the redundancy-based sensor fault diagnostic methods, this chapter introduces a fault-tolerant voltage measurement method that can distinguish between a sensor fault and a battery cell fault without any additional sensors or modeling work. Instead of measuring the voltage values of individual cells, the voltage sensors are used to measure the voltage sum of multiple cells. In this way, a cell voltage value is linked with multiple voltage sensors. When a cell fault occurs, its corresponding voltage sensors will indicate the fault at the same time, thereby identifying the fault. The basic interleaved voltage measurement method is first introduced to demonstrate the working principle and validity of the method, and the constraint in the sensor topology is investigated. Then the improved voltage measurement method is proposed such that the coprime constraint in the sensor topology is removed and the noise is mathematical formulated.
5.2 The basic interleaved voltage measurement method

5.2.1 A fault-tolerant design

The drawback of the prevailing voltage measurement method lies in its one-to-one correspondence of voltage sensors and cell voltages, as shown in Figure 5.1a. In real applications, the voltage sensors have their own reliability, and thus a sensor fault may lead to a false positive cell failure detection.

In many industry applications, a second sensor is added to each measurement to provide the redundancy. The data from the second group of sensors will provide validation of the measurement of the first group. Figure 5.1b shows its embodiment if applied to voltage monitoring for series connected battery packs. The sensors can tell the cell fault in case both sensors give consistent outputs. When the two sensors corresponding to the same cell have different readings, we normally treat it as a sensor fault. However, this method adds significant cost to the system. In particular, the battery packs in EVs consists of hundreds of cells in series. Therefore, the redundancy sensors can add significant cost to the hardware system.

One common solution to this problem is to add a sensor redundancy within a group of measurements, as shown in Figure 5.1c, in which a string voltage sensor is added in addition to the five voltage sensors for the cells. This method improves cell failure detection, but it still cannot distinguish between sensor failure and cell failure when the sensors show inconsistent readings. For example, if the nominal voltage of the five cells in Figure 5.1c is 3 V, $V_1$ shows 0 V, $V_2$ through $V_5$ show 3 V and $V_6$ shows 15 V, the fault diagnostic result is different depending on which voltage sensor is trusted. When $V_1$ is trusted, it indicates $C_1$ is in ESC condition and $V_6$ is stuck at 15 V due to circuit failure. When $V_6$ is trusted, it indicates that $V_1$ is in sensor fault condition and $C_1$ is in normal condition. Another voltage measurement topology is illustrated in Figure 5.1d. This topology measures an accurate reference voltage from an integrated chip as the last measurement in one sampling period, which can be used to calibrate sensor offset and detect sensor fault. However, this method requires a precision voltage reference chip for each of the voltage measurement circuit, and it
(a) The prevailing voltage measurement method.

(b) Cell level redundancy.

(c) String level redundancy.

(d) Voltage calibration.

Figure 5.1: Schematics of different battery sensor topology.
increases the voltage update period by one clock cycle. Except that, this method will always attribute switch/trace malfunction to cell fault.

**Design description**

Figure 5.2 illustrates one embodiment of the proposed fault-tolerant voltage measurement method. In this topology, each voltage sensor measures the voltage sum of two cells, including V5, which measures the voltage sum of C1 and C5. The schematic in Figure 5.2 ensures that the voltage of each cell is associated with the measurements of two sensors. For example, the voltage value of C2 is included in the measurements of V1 and V2. When C2 is in ESC condition, its terminal voltage drops to zero, and its abnormal voltage value will be revealed by V1 and V2 as they both drop from 6 V to 3 V. On the other hand, when a sensor fault occurs, it can be identified immediately in that it is impossible for only one of the sensed voltage values to change. For example, if V1 through V5 show 6 V, and suddenly only V2...
changes from 6 V to 0 V, V2 is certainly in fault condition, otherwise the voltage values of C1 and C4 will be 6 V, and C5s will be 0 V. The latter condition involves the same overcharge level on C1 and C4 and an external circuit fault on C5, which are almost impossible to occur at the same time.

Matrix interpretation of measurement topologies

The relation between sensor measurements V and cell voltage values C can be expressed as

\[ V = AC \]  \hspace{1cm} (5.1)

where V is an \( n \times 1 \) matrix that includes all the readings from the voltage sensors, C is an \( n \times 1 \) matrix that includes all the voltage values for the cells in the series connection, and A is an \( n \times n \) matrix that correlates V with C.

For the schematics in Figure 5.1a, equation (5.1) can be written as (5.2). The A matrix of (5.2) demonstrates that each cell voltage corresponds to one voltage sensor. In other words, when a cell fault occurs, only its corresponding voltage sensor can be used to indicate the cells status. This is also true when the C matrix is calculated from the V matrix, as shown in (5.3), in which each sensor reading correlates to only one cell voltage. When a sensor is in fault condition, it is hard to distinguish sensor failure from cell failure.

\[
\begin{bmatrix}
V_1 \\
V_2 \\
V_3 \\
V_4 \\
V_5 \\
C_1 \\
C_2 \\
C_3 \\
C_4 \\
C_5
\end{bmatrix} = 
\begin{bmatrix}
1 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 1 \\
1 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
C_1 \\
C_2 \\
C_3 \\
C_4 \\
C_5
\end{bmatrix}
\]  \hspace{1cm} (5.2)

\[
\begin{bmatrix}
C_1 \\
C_2 \\
C_3 \\
C_4 \\
C_5
\end{bmatrix} = 
\begin{bmatrix}
1 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
V_1 \\
V_2 \\
V_3 \\
V_4 \\
V_5
\end{bmatrix}
\]  \hspace{1cm} (5.3)

The A matrix of the proposed method in Figure 5.2 is shown in (5.4). By observing the columns of the A matrix, it can be found that the voltage value for
each cell is linked to two voltage sensors. For example, the two ‘1’s in the third column of (5.4) indicate that the voltage value of $C_3$ is included in both $V_2$ and $V_3$. This feature ensures that when cell failure occurs, it will be revealed by two sensors. The probability of two sensors exhibiting the same sensor fault at the same time is a low probability, therefore cell failure can be determined with high confidence. Similarly, $A^{-1}$ in (5.5) indicates that when a sensor fault occurs, the abnormal change in the voltage sensor is to be reflected by multiple calculated cell values. In addition, some of the changes in the cell voltage values are positive to the sensor change and some of the changes in cell voltage values are negative to the sensor change. This feature further increases the sensor fault diagnostics credibility because simultaneous voltage changes in different directions with the same amplitude at the same time are extremely abnormal in series connected packs.

\[
\begin{bmatrix}
V_1 \\
V_2 \\
V_3 \\
V_4 \\
V_5
\end{bmatrix} =
\begin{bmatrix}
1 & 1 & 0 & 0 & 0 \\
0 & 1 & 1 & 0 & 0 \\
0 & 0 & 1 & 1 & 0 \\
0 & 0 & 0 & 1 & 1 \\
1 & 0 & 0 & 1 & 0
\end{bmatrix}
\begin{bmatrix}
C_1 \\
C_2 \\
C_3 \\
C_4 \\
C_5
\end{bmatrix}
\]

(5.4)

\[
\begin{bmatrix}
C_1 \\
C_2 \\
C_3 \\
C_4 \\
C_5
\end{bmatrix} =
\begin{bmatrix}
\frac{1}{2} & -\frac{1}{2} & \frac{1}{2} & -\frac{1}{2} & \frac{1}{2} \\
\frac{1}{2} & \frac{1}{2} & -\frac{1}{2} & \frac{1}{2} & -\frac{1}{2} \\
-\frac{1}{2} & \frac{1}{2} & \frac{1}{2} & -\frac{1}{2} & \frac{1}{2} \\
\frac{1}{2} & -\frac{1}{2} & \frac{1}{2} & \frac{1}{2} & -\frac{1}{2} \\
-\frac{1}{2} & \frac{1}{2} & -\frac{1}{2} & \frac{1}{2} & \frac{1}{2}
\end{bmatrix}
\begin{bmatrix}
V_1 \\
V_2 \\
V_3 \\
V_4 \\
V_5
\end{bmatrix}
\]

(5.5)

5.2.2 Fault isolation

The fault cell can be located based on the locations of sensors showing abnormal values. If the cell failure is modeled as the sum of normal cell voltages and the effect of fault conditions, it can be expressed as

\[
C = C_{\text{normal}} + C_{\text{fault}}
\]

(5.6)
where $C_{\text{normal}}$ is the cell voltage values in normal working condition, and $C_{\text{fault}}$ is the impact of the fault conditions. $C_{\text{fault}}$ can be isolated by

$$C_{\text{fault}} = C - C_{\text{normal}} = A^{-1}V - C_{\text{normal}}$$ (5.7)

where $V$ is the voltage readings after the fault occurs and $C_{\text{normal}}$ is the cell voltages in normal conditions. When $C_{\text{fault}}$ is determined, the indices of cells in fault condition are found and their influence on normal voltage values is also determined.

Likewise, the sensor fault location can be determined according to the indices of cells with abnormal voltage variations. If the sensor failure is modeled as the sum of the sensor reading under normal condition and the effect of fault conditions, it can be expressed as

$$V = V_{\text{normal}} + V_{\text{fault}}$$ (5.8)

where $V_{\text{normal}}$ is the normal reading and $V_{\text{fault}}$ is the impact of the fault conditions. $V_{\text{fault}}$ can be isolated by

$$V_{\text{fault}} = V - V_{\text{normal}} = V - AC_{\text{normal}}$$ (5.9)

When $V_{\text{fault}}$ is determined, the index of the sensor in fault condition can be found and its influence on normal sensor readings is determined.

5.2.3 Simulation

The simulation is set up to test the viability of the proposed fault-tolerant voltage measurement method. A SIMSCAPE model is built for a battery pack consisting of five battery cells in series connection. In order to demonstrate the robustness of the method in dynamic situation, the UDDS cycle is applied to the battery pack when the faults are induced.

An ESC fault on $C_3$ is induced at 300 s by reducing $C_3$ by 2 V. The simulation results are shown in Figure 5.3. It needs to be noted that the reduction in voltage is assigned qualitatively and is only used to demonstrate the viability of the proposed method. At 300 s, the readings of $V_2$ and $V_3$ drop by 2 V, indicating a sudden 2 V voltage drop in the overlap of $V_2$ and $V_3$. Clearly, $C_3$ is the overlap and it is demonstrated by the calculated cell terminal voltages.
Figure 5.3: ESC simulation for $C_3$ at 300 s.
Figure 5.4: Sensor fault simulation for $V_2$ at 300 s.
A same conclusion can be drawn by comparing $V_{\text{fault}}$ and $C_{\text{fault}}$ signals provided in Figure 5.3c and 5.3d. $V_{\text{fault}}$ indicates two sensor faults on both $V_2$ and $V_3$ at 300 s, while $C_{\text{fault}}$ flags a sudden 2 V voltage drop on $C_3$. There are two possible explanation: 1) Two sensor faults happen at 300 s and these lead to wrong voltage calculation on $C_3$; 2) $C_3$ is in external circuit fault and this leads abnormal readings on both $V_2$ and $V_3$. Clearly, the latter explanation is more convincing because it is less likely for two sensors to go wrong at the same sampling period.

Similarly, the sensor fault is simulated by setting $V_2$ to zero after 300 s. The simulation results are shown in Figure 5.4. With wrong reading from $V_2$ after 300 s, the five voltage values all turns abnormal. The offset of the cell voltages follows the trend shown by the second column of (5.5), leading the system to flag a sensor fault to $V_2$ at 300 s, instead of five abnormal cell faults.

### 5.2.4 Experiment

Experiments are set up to demonstrate the concept of the proposed method. A circuit board is built based on the diagram in Figure 5.2, as shown in Figure 5.5. The schematic of the experimental setup is shown in Figure 5.6. The voltage sum of two separate cells in series can be realized in hardware by the circuit given in Figure 5.7. The positive and negative terminals of the first cell are connected to $V_{1+}$ and $V_{1-}$. The second separate cell is connected to $V_{2+}$ and $V_{2-}$. By properly choosing the resistors, i.e., $R = R_1 = R_2 = R_3 = R_4 = R_f$ and $R_h = R_q R/(R_q + R)$, the output will be the inverse of the sum of the two voltage values, i.e. $V_o = -(V_{1+} - V_{1-} + V_{2+} - V_{2-})$. It needs to be noted that the only added cost of the circuit in Figure 5.7 compared to commercial differential amplifiers is an additional pair of resistors, i.e., $R_3$ and $R_4$, which is negligible.

An ESC fault is induced by shorting $C_2$ with a relay. The resistance of the wires and relay is 0.87 Ω. The ESC lasts for 1 s and then the relay is opened. Experiment results in Figure 5.8a show that $V_1$ and $V_2$ indicate abnormal voltage changes at 232.8 s and lasting for 1 s. The calculated cell voltage values in Figure 5.8b demonstrate that $C_2$ shows abnormal voltage values at 232.8 s lasting for 1 s. In this situation, it is obvious that the probability of two sensors experiencing the same sensor fault
at the same time is much lower than that of one cell undergoing an ESC. The fault signal in Figure 5.8d indicates an abnormal voltage drop in $C_2$. Thus, a cell fault is determined.

The sensor fault is induced by disconnecting the jump wire in the sensing path of $V_4$ on the bottom side of the circuit board. Experiment results in Figure 5.9b shows that the calculated cell voltages demonstrate abnormal values at 233.1 s. The voltage values of $C_1$ and $C_3$ are increased, while those of $C_2$, $C_4$ and $C_5$ are decreased. These changes are of same magnitude and the signs follows those of the fourth column of (5.5). As a result, the sensor fault on $V_4$ is determined.
Figure 5.6: Schematic of experimental setup.

Figure 5.7: Circuit realization of voltage sum of separate cells.
Figure 5.8: ESC experiment for $C_2$ at 232.8 s.
Figure 5.9: Sensor fault experiment for $V_4$ at 233.1 s.
5.2.5 Generalization of the problem

The proposed voltage measurement method can be extended to a battery pack with \( n \) cells in series, in which each voltage sensor measures the voltage sum of \( k \) cells \((k < n)\). It needs to be noted that, given the measurement circuit in Figure 5.7, the \( n \) cells can be nonconsecutive, as demonstrated in (5.10) and (5.11), so long as the \( A \) matrix is invertible. It is interesting to see that the prevailing sensing topology is a special case of this general topology with \( k = 1 \).

\[
\begin{bmatrix}
V_1 \\
V_2 \\
V_3 \\
V_4 \\
V_5
\end{bmatrix} =
\begin{bmatrix}
1 & 0 & 1 & 0 & 0 \\
0 & 1 & 0 & 1 & 0 \\
0 & 0 & 1 & 0 & 1 \\
1 & 0 & 0 & 1 & 0 \\
0 & 1 & 0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
C_1 \\
C_2 \\
C_3 \\
C_4 \\
C_5
\end{bmatrix} \tag{5.10}
\]

\[
\begin{bmatrix}
C_1 \\
C_2 \\
C_3 \\
C_4 \\
C_5
\end{bmatrix} =
\begin{bmatrix}
\frac{1}{2} & -\frac{1}{2} & -\frac{1}{2} & \frac{1}{2} & \frac{1}{2} \\
\frac{1}{2} & \frac{1}{2} & -\frac{1}{2} & -\frac{1}{2} & \frac{1}{2} \\
\frac{1}{2} & \frac{1}{2} & \frac{1}{2} & -\frac{1}{2} & -\frac{1}{2} \\
-\frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & -\frac{1}{2} \\
-\frac{1}{2} & -\frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2}
\end{bmatrix}
\begin{bmatrix}
V_1 \\
V_2 \\
V_3 \\
V_4 \\
V_5
\end{bmatrix} \tag{5.11}
\]

\[
\begin{bmatrix}
V_1 \\
V_2 \\
\vdots \\
V_{n-k+1} \\
V_{n-k} \\
V_n
\end{bmatrix} =
\begin{bmatrix}
1 & \cdots & \cdots & 1 & 0 & \cdots & \cdots & 0 \\
0 & 1 & \cdots & \cdots & 1 & 0 & \cdots & \cdots & 0 \\
\vdots & \vdots & \ddots & \cdots & \ddots & \cdots & \ddots & \cdots & \ddots \\
0 & \cdots & \cdots & 0 & 1 & \cdots & \cdots & 1 \\
1 & 0 & \cdots & \cdots & 0 & 1 & \cdots & 1 \\
\vdots & \vdots & \ddots & \cdots & \ddots & \cdots & \ddots & \ddots & \ddots \\
1 & \cdots & 1 & 0 & \cdots & \cdots & 0 & 1
\end{bmatrix}
\begin{bmatrix}
C_1 \\
C_2 \\
\vdots \\
C_{n-k+1} \\
C_{n-k} \\
C_n
\end{bmatrix} \tag{5.12}
\]

Indeed, the previously demonstrated combination of \( n = 5 \) and \( k = 2 \) may not be the optimal solution for EV packs, whose \( n \) may exceed several hundreds. The measurement topology can be generalized to the case where the voltage sensors measure the sum of \( k \) consecutive cell voltages \( 2 \leq k < n \), as indicated in (5.12).
5.3 The improved interleaved voltage measurement method

5.3.1 Invertibility of the measurement matrix

In this section, a proof is presented for the invertibility condition of the $A$ matrix in the form of (5.12). The new proof is not only more concise, but also sheds light on the performance improvement for the interleaved sensor topology, which is covered in later sections.

Proposition 1: A matrix is invertible if and only if its determinant is nonzero [74].

Combined with the following property of the determinant

$$\det(A) = \prod_{i=0}^{n-1} \lambda_i$$  \hspace{1cm} (5.13)

where $\lambda_i$ is the $(i+1)^{th}$ eigenvalue of an $n \times n$ matrix, the next proposition is obtained.

Proposition 2: A matrix is invertible if and only if none of its eigenvalues is zero.

Now, we need to introduce the concept of the circulant matrix. A circulant matrix is a special kind of matrix, where each row is rotated one element to the right relative to the preceding row [75]. Indeed, the $A$ matrix is a circulant matrix. The basic properties of the circulant matrix give the following proposition.

Proposition 3: The eigenvalues of the circulant matrix are the discrete Fourier transform (DFT) of its first row [76].

Denote the first row of an $n \times n$ circulant matrix as $[a_0, a_1, \cdots, a_{n-1}]$, then according to Proposition 3, the eigenvalues of (5.12) can be expressed as

$$\lambda_i = \sum_{m=0}^{n-1} a_m e^{-j \frac{2\pi}{n} im} = \sum_{m=0}^{k-1} e^{-j \frac{2\pi}{n} im}, i = 0, 1, \cdots, n - 1$$  \hspace{1cm} (5.14)

where $j$ is the unit imaginary number. Since the eigenvalues are sums of geometric series, their expressions can be simplified as

$$\lambda_i = \left\{ \begin{array}{ll} k & \text{if } i = 0 \\ \frac{k}{1-e^{-j \frac{2\pi}{n} i}} & \text{if } i \neq 0 \end{array} \right.$$  \hspace{1cm} (5.15)
By Proposition 2, the invertibility of (5.12) is ensured when none of the eigenvalues in (5.12) is zero. Clearly, the eigenvalue is nonzero when \( i = 0 \). When \( i \neq 0 \),

\[
\lambda_i = 0 \iff 1 - e^{-j\frac{2\pi}{n}ik} = 0 \iff e^{-j\frac{2\pi}{n}ik} = 1
\]  

(5.16)

In order to keep all eigenvalues nonzero, it requires

\[
\frac{2\pi}{n} ik \neq 2p\pi \iff ik \neq pn, \text{ for any } i = 1, 2, \cdots, n - 1 \text{ and any } p \in \mathbb{N}
\]  

(5.17)

The statement of (5.17) is equivalent to examine whether the multiple of \( k \) is also a multiple of \( n \). It shows that none of the \( ik \) is a multiple of \( n \) for \( i = 1, 2, \cdots, n - 1 \), or none of them is a common multiple of \( n \) and \( k \). It is universally acknowledged that \( nk \) is a common multiple of both \( n \) and \( k \), and when (5.17) is true, \( nk \) is also the least common multiple of \( n \) and \( k \). This fact indicates \( n \) and \( k \) are coprime.

5.3.2 Graphical interpretation of the choice of \( n \) and \( k \)

The first row of (5.12) consists of \( k \) consecutive 1s followed by \((n - k)\) consecutive 0s. Its eigenvalues can be visualized by plotting the DFT of its first row versus the angle \( 2\pi \frac{i}{n}, i = 0, 1, \cdots, n - 1 \) as Figure 5.10. When \( k \) is fixed and \( n \) is a very large number, the profile of the eigenvalues can be obtained for this specific \( k \). Then the eigenvalues of a small \( n^* \) are the corresponding values at \( 2\pi \frac{i}{n^*}, i = 0, 1, \cdots, n^* - 1 \) on the profile.

As an example, the solid line in Figure 5.10 shows the case of \( n = 100 \) and \( k = 4 \). The stems in Figure 5.10 give the eigenvalues of \( n = 5 \) and \( k = 4 \). It can be seen that the eigenvalues of \( n = 5 \) and \( k = 4 \) are \((4, 1, 1, 1, 1)\). Since none of these eigenvalues is zero, the combination of \( n = 5 \) and \( k = 4 \) is invertible, and the corresponding measurement topology works.

It is interesting to note that there are three potential points on the profile, where the values are zero. If any of the stems falls on the zero points, it will lead to noninvertible measurement matrix and the corresponding measurement topology does not work. In general, the eigenvalue profile on the horizontal span is divided into \( k \) parts by the \( k - 1 \) evenly distributed zero points. If \( n \) is a multiple of \( k \), then
there must exist an $i$ such that $\frac{i}{n} = \frac{1}{k}$, and this $i$ will place a stem at one of the zero points.

If the derivation from (5.14) to (5.17) is revisited, it is clear that the first eigenvalue will never be zero. As long as $k$ is not a factor of $n$, the stems will never fall on the zero points on the profile. The graphical interpretation matches the previous derivation and assists us to visualize the $n$ and $k$ choices.

5.3.3 Extension based on graphical interpretation

Based on the mathematical analysis and the graphical interpretation, it proves that $n$ and $k$ need to be relative prime for the basic interleaved measurement matrix as (5.12). In real battery applications, the number of batteries in a module, or $n$, is usually a multiple of 6 or 12. This is because these two numbers have many factors and it simplifies the pack design and assembly. Nevertheless, many of the factors are not favored in the measurement topology as shown in (5.12), because these factors cannot be used as $k$ to construct a valid measurement topology. For example, if the number of cells in a module is 12, then the only choices for $k$ are 5, 7 and 11. The high value of $k$ choices causes 1) more complicated hardware implementation; 2)
higher voltage range for each sensor; 3) higher noise level compared with that of the traditional topology. In this section, an improved measurement matrix is proposed such that the constraint is removed.

The graphical interpretation shows that the limitation of \( n \) and \( k \) choices is caused by the zero points in the DFT profile. In other words, if the DFT profile is not zero anywhere over the \( 2\pi \) span, then the corresponding \( A \) matrix should be always invertible.

![Figure 5.11: Different DFT plot for \( k=2 \).](image-url)

As the case of two nonzero first row entries, the two entries can be normalized to be \( a_0 = 1 \), and \( a_1 = q, (q > 0) \). As an example, the DFT profiles of \( q = 1 \) and \( q = 0.5 \) are given in Figure 5.11. It shows that, when \( q = 1 \), which is the case of (5.12), the dashed profile equals to zero when the angle equals to \( \pi \), whereas the solid line does not equal to zero anywhere over the horizontal span. This is because the zero eigenvalue emerges when

\[
\lambda_i = a_0 + a_1 e^{-j \frac{2\pi}{n} i} = 1 + q e^{-j \frac{2\pi}{n} i} = 0, \text{ for } i = 0, 1, \cdots, n-1 \quad (5.18)
\]

In the case of \( q = 1 \), \( \lambda_i \) is zero when the angle is \( \pi \), leaving the \( A \) matrix noninvertible. However, this situation can be easily improved by assigning different values for \( a_0 \) and \( a_1 \). Consequently, the DFT profile will never touch zero, and the
resulting $A$ matrix is always invertible no matter what $n$ value is chosen. Therefore, for the special case of two nonzero row entries, the $A$ matrix is always invertible regardless of the choice of $n$ when $a_0/a_1 \neq 1$.

Actually, this design can be extended to other number of nonzero entries as well. The ultimate goal is to ensure none of the eigenvalues is zero. In more general cases, the row entries in geometric series guarantee the invertibility of $A$ for any combination of $n$ and $k$, as

$$a_i = \begin{cases} q_i & i = 0, 1, \cdots, k - 1, q > 0 \text{ and } q \neq 1 \\ 0 & k \leq i \leq n - 1 \end{cases}$$

(5.19)

5.3.4 Hardware implementation

Voltage sum of separate cells

The realization of the interleaved topology is limited to the hardware implementation. The first problem is that the voltage sum of cells is hard to obtain when they are separated by other cells, which is needed as the realization of the last row of (5.12).

The previous section has proposed a circuit that calculates the separate voltage sum with additional pairs of resistors compared with the classic differential amplifiers, as given in Figure 5.12, where $V_{i+}$ and $V_{i-}$ connect to the positive and negative

![Figure 5.12: Measurement circuit for voltage sum calculation of separate cells.](image-url)
terminals of battery cells. With slight modification, it can be used to realize the case with different nonzero entries. For example, if there are only two separate cells, 
\[ V_o = -[(V_1 + V_{1-}) + q(V_{2+} - V_{2-})] \]
can be realized when the resistor values follow the relation as

\[ R_1 = R_f, R_2 = \frac{1}{q} R_f, R_h = \frac{R_f R_g}{R_f + R_g} \quad (5.20) \]

**Number of switches**

The typical sequential voltage measurement circuit is given in Figure 5.13 [77]. It shows that the conventional measurement topology requires \(2n\) switches because two terminals conduct to the measurement circuit at each sampling interval.

![Figure 5.13](image)

**Figure 5.13:** The conventional measurement topology requires \(2n\) switches.

For the measurement topology of (5.12), a same number of switches are needed, because the consecutive cell measurements also need two terminals conducting to the measurement circuit within one sampling, as shown in Figure 5.14a. If the row entries of the \(A\) matrix are not the same, the number of switches needs to be increased due to an additional path to the measurement circuit within each sampling as shown in Figure 5.14b. Given different row entries, this additional path provides more information from the cell voltages, which is the key to make the measurement matrix invertible. In the general case of (5.19), where the first row entries are different
and consecutive, the number of switches increases as $k$ increases. Thus, from the cost perspective, the choice of two nonzero entries is most favored in the interleaved voltage measurement topology.

![Diagram](image)

(a) The basic interleaved topology

![Diagram](image)

(b) The improved interleaved topology

**Figure 5.14:** Circuits implementation for voltage measurements.

### 5.3.5 Reliability analysis

The voltage measurement system can be modeled as a series connected system [78], where each voltage sensor is one of the subsystems. Only when all the subsystems are functioning well, the whole system is in normal condition. If any of the subsystems fails, the whole system fails and a fault is flagged.

The reliability of a voltage sensor is modeled as a device with constant failure rate, as shown in

$$R_s(t) = e^{-\lambda t}, \lambda > 0$$  \hspace{1cm} (5.21)
where $R$ is the reliability of a voltage sensor, $\lambda$ is the constant failure rate and all the voltage sensors are assumed to have the same failure rate.

When the sensor fault does not occur, the proposed method works the same as traditional one-to-one correspondence measurement topology does. However, when the sensor fault occurs, the traditional method flags a cell fault, but the proposed method flags sensor fault unless all the associated sensors are in fault condition within the same sampling period. The confidence level of the sensor fault detection from the proposed method can be expressed as

$$CL = 1 - P(k \text{ sensor fail}|1 \text{ sensor fails}) = 1 - \frac{\prod_{i=1}^{k} \int_{t=0}^{T_s} f_i(t) \, dt}{\int_{t=0}^{T_s} f_i(t) \, dt} = 1 - \prod_{i=1}^{k-1} \int_{t=0}^{T_s} (1 - e^{-\lambda t}) \, dt$$

(5.22)

where $CL$ is the confidence level of the sensor fault detection ranging from 0 to 1, $T_s$ is the sampling period of the voltage measurements, $f_i(t)$ is the failure density of voltage sensor $i$, and $j$ is an arbitrary number within 1 and $k$. The relation between $f_i(t)$ and $R_i(t)$ is given by [79].

$$R_i(t) + F_i(t) = 1 \quad (5.23)$$

$$f(t) = \frac{d}{dt} F(t) \quad (5.24)$$

where $F_i(t)$ is the unreliability of voltage sensor $i$.

There are two key points that needs to be pointed out from (5.22),

i) The larger the $k$ is, the more confidence the BMS has in the sensor fault detection. In the traditional voltage measurement topology as shown in Figure 5.1a, $k$ is 1. This leads the $CL$ value drop to zero when the sensor fault occurs, which indicates that the traditional topology gives a false cell fault detection whenever a sensor fault occurs. As for the proposed method, $k$ is larger than 1, which significantly increases the $CL$ value. This is the key to improve the fault detection confidence.

ii) The smaller the $T_s$ is, the more confidence in the fault detection. This is due to the monotonic increase of the integral of failure intensity. In practice, it refers
to the fact that it is less possible for multiple sensors to fail within a shorter period of time.

The above two points are illustrated in Figure (5.15), where the $CL$ values are plotted with different sampling times and different $k$’s. With a fixed $k$, the detection confidence decreases as $T_s$ increases. With a fixed $T_s$, the detection confidence increases as $k$ increases. Since the typical sampling period for BMS is smaller than 1 s, the inset in Figure 5.15 gives detailed figure for $T_s$ smaller than 1 s. The result shows that, when the sensor fault occurs, the proposed method can eliminate more than 98% of the false cell fault detection.

![Figure 5.15:](image)

**Figure 5.15:** Fault detection reliability increases as i) $k$ increases ii) $T_s$ decreases. ($\lambda=0.02/s$)

### 5.3.6 Noise analysis

**General analysis of noise level gain**

The noise of the voltage sensors can be modeled as the white noise with a zero mean value and a standard deviation of $\sigma$. Here we assume that: 1) $\sigma$ is the noise standard deviation of the voltage sensor whose range covers a typical cell voltage; 2)
the noise standard deviation is proportional to the number of series cells it measures;
3) the noises of different voltage sensors are uncorrelated. Then the variance of the
sensor measurement can be expressed as

$$\text{Var}(V_i) = \sum_{p=0}^{n-1} (a_p \sigma)^2, \ i = 0, 1, \cdots, n - 1 \quad (5.25)$$

The noise level gain, $G_{NL}$, is defined as the noise standard deviation of the cell
voltages obtained from the interleaved topology divided by that of the conventional
topology. With Proposition 4, denote the row entries of the inverse of $A$ matrix as
$[b_0, b_1, \cdots, b_{n-1}]$, then the noise level gain can be derived as

$$G_{NL} = \sqrt{\frac{\text{Var}(\sum_{i=0}^{n-1} b_i V_i)}{\sigma^2}} = \sqrt{\frac{\text{Var}(V_i) \sum_{i=0}^{n-1} b_i^2}{\sigma^2}} = \sqrt{\frac{\left(\sum_{i=0}^{n-1} a_i^2 \sum_{i=0}^{n-1} b_i^2\right)}{\sigma^2}} \quad (5.26)$$

**Proposition 4**: The inverse of an invertible circulant matrix is also a circulant matrix
[80].

It is discussed in [81] that the general solution of the inverse of a circulant
matrix is given as

$$b_i = \sum_{m=0}^{n-1} n(a_0 + a_1 e^{j \frac{2m \pi}{n}} + \cdots + a_{n-2} e^{-j \frac{4m \pi}{n}} + a_{n-1} e^{-j \frac{2m \pi}{n}}), \ i = 0, 1, \cdots, n - 1 \quad (5.27)$$

where $b_i$ is the $i^{th}$ first row entry of the inverse of $A$ matrix, and denote the inverse
of $A$ matrix as $B$.

For simplicity, $b_i$ is expressed as an $n \times n$ matrix as (5.28). If the entry in
the $(i+1)^{th}$ row and $(m+1)^{th}$ column is denoted as $\beta_{i,m}$, then when $i = 0$, the
numerators of $\beta_{0,m}$, $m = 0, 1, \cdots, n - 1$, are 1; when $m = 0$, the exponential terms
in the denominators are 1. Next, the matrix representation of $b$ is used to prove a proposition.

$$\begin{bmatrix} b_0 \\ b_1 \\ \vdots \\ b_{n-1} \end{bmatrix} = \begin{bmatrix} \frac{1}{n} \sum_{p=0}^{n-1} a_p e^{j \frac{2p \pi}{n}} & \frac{1}{n} \sum_{p=0}^{n-1} a_p e^{j \frac{2p \pi}{n}} & \cdots & \frac{1}{n} \sum_{p=0}^{n-1} a_p e^{j \frac{2(n-1) \pi}{n}} \\ \frac{1}{n} \sum_{p=0}^{n-1} a_p e^{j \frac{2p \pi}{n}} & \frac{1}{n} \sum_{p=0}^{n-1} a_p e^{j \frac{2p \pi}{n}} & \cdots & \frac{1}{n} \sum_{p=0}^{n-1} a_p e^{j \frac{2(n-1) \pi}{n}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{1}{n} \sum_{p=0}^{n-1} a_p e^{j \frac{2p \pi}{n}} & \frac{1}{n} \sum_{p=0}^{n-1} a_p e^{j \frac{2p \pi}{n}} & \cdots & \frac{1}{n} \sum_{p=0}^{n-1} a_p e^{j \frac{2(n-1) \pi}{n}} \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix} \quad (5.28)$$
Proposition 5: The sum of the row entries of $B$ matrix equals the inverse of the sum of the row entries of $A$ matrix.

First, this proposition can be proved by assigning special values to cell voltages. When $C_i = 1$, for $i = 1, 2, \cdots, n$, $V_i = \sum_{p=0}^{n-1} a_p$ as (5.29). As $C_i$ is calculated from $B$ matrix as (5.30), the equation indicates $\sum_{p=0}^{n-1} a_p \sum_{p=0}^{n-1} b_p$.

$$\begin{bmatrix} V_1 \\ V_2 \\ \vdots \\ V_n \end{bmatrix} = \begin{bmatrix} a_0 & a_1 & \cdots & a_{n-1} \\ a_{n-1} & a_0 & a_1 & \cdots \\ \vdots & \vdots & \ddots & \vdots \\ a_1 & \cdots & a_{n-1} & a_0 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix}$$ (5.29)

$$\begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix} = \begin{bmatrix} b_0 & b_1 & \cdots & b_{n-1} \\ b_{n-1} & b_0 & b_1 & \cdots \\ \vdots & \vdots & \ddots & \vdots \\ b_1 & \cdots & b_{n-1} & b_0 \end{bmatrix} \begin{bmatrix} V_1 \\ V_2 \\ \vdots \\ V_n \end{bmatrix}$$ (5.30)

Proposition 5 can also be proved by (5.28) in a straightforward way. Except the first column, the sum for each column equals to 0. The sum of $B$ matrix then equals the sum of the first column and the result is $1/\sum_{p=0}^{n-1} a_p$, which is the inverse of the sum of row entries of $A$ matrix.

The same technique can be applied to calculate the sum of $b_i^2$, which is an essential part of $G_{NL}$. An $n \times (n + C_n^2)$ matrix is constructed as (5.31), where $C_n^2$ is the number of combination sets for choosing 2 objects from $n$ distinct objects.

$$\begin{bmatrix} \beta_{0,0}^2 & \cdots & \beta_{0,n-1}^2 & 2\beta_{0,0}(1)\beta_{0,0}(2) & \cdots & 2\beta_{0,0}(1)\beta_{0,n-1}(2) \\ \beta_{1,0}^2 & \cdots & \beta_{1,n-1}^2 & 2\beta_{1,0}(1)\beta_{1,0}(2) & \cdots & 2\beta_{1,0}(1)\beta_{1,n-1}(2) \\ \vdots & \cdots & \vdots & \vdots & \ddots & \vdots \\ \beta_{n-1,0}^2 & \cdots & \beta_{n-1,n-1}^2 & 2\beta_{n-1,0}(1)\beta_{n-1,0}(2) & \cdots & 2\beta_{n-1,0}(1)\beta_{n-1,n-1}(2) \end{bmatrix}$$ (5.31)

where $\delta_i \in S_n$, $S_n$ is the set of all combinations of choosing 2 values from 0, 1, $\cdots$, $n-1$, and $\delta_i$ is one of the combination within $S_n$.

It can be observed from the $n \times (n + C_n^2)$ matrix that every entry is closely
related to the product of $\beta$. For a given column, its entries can be expressed as
\[
\alpha \beta_{i,u} \beta_{i,v} = \alpha \frac{\sum_{p=0}^{n-1} a_p e^{j2\pi u p/n}}{n \sum_{p=0}^{n-1} a_p e^{j2\pi u p/n}} \frac{1}{n \sum_{p=0}^{n-1} a_p e^{j2\pi v p/n}} = \frac{\alpha}{n^2} \sum_{p=0}^{n-1} a_p e^{j2\pi (u+v) p/n}
\]
(5.32)
where $0 \leq u \leq v \leq n-1$, and $\alpha$ depends on the column index $m$ (note $m$ starts from 0) as
\[
\alpha = \begin{cases} 
1 & m = 0, 2, \ldots, n-1 \\
2 & m = n, \ldots, n + C^2_n - 1 
\end{cases}
\]
(5.33)

There are two important facts for (5.32): 1) the denominators are the same for the same column; 2) the common ratio of the numerators for the same column is $e^{j2\pi (u+v)/n}$. Thus, the sum of a column can be written as
\[
\alpha \sum_{i=0}^{n-1} \beta_{i,u} \beta_{i,v} = \begin{cases} 
\sum_{i=0}^{n-1} a_p e^{j2\pi u p/n} \sum_{i=0}^{n-1} a_p e^{j2\pi v p/n} \frac{\alpha}{n^2} & = 1 \\
0 & \neq 1
\end{cases}
\]
(5.34)

It shows that so long as the common ratio is not 1, the sum of one column is 0. For an odd number of $n$, there are two possible situations where the common ratio is 1: 1) when $m \leq n - 1$, $u = v = 0$; 2) when $m > n - 1$, $u + v = n$. Obviously, the number for case 1) is 1, and the number for case 2) is $(n-1)/2$. Combined with similar cases where $n$ is an even number, the Cauchy-Schwarz inequality in (5.35) leads to (5.36), (5.37) and finally Proposition 6.

\[
\sum_{p=0}^{n-1} a_p e^{j2\pi p/n} \sum_{p=0}^{n-1} a_p e^{j2\pi (-p)/n} = \sum_{p=0}^{n-1} a_p e^{j2\pi p/n} \sum_{p=0}^{n-1} a_p e^{-j2\pi p/n} \geq \left( \sum_{p=0}^{n-1} a_p \right)^2
\]
(5.35)

\[
\sum_{i=0}^{n-1} b_i^2 = \frac{1}{n(\sum_{p=0}^{n-1} a_p)^2} + 2 \frac{1}{n(\sum_{p=0}^{n-1} a_p)^2} + \cdots \\
+ 2 \frac{1}{n \sum_{p=0}^{n-1} a_p e^{j2\pi p/n} (n^2 - 1) \sum_{p=0}^{n-1} a_p e^{j2p(n-1)/n} (n+1)}
\]
(5.36)

\[
> \frac{1}{n(\sum_{p=0}^{n-1} a_p)^2} + 2 \frac{1}{n(\sum_{p=0}^{n-1} a_p)^2} + \cdots + 2 \frac{1}{n(\sum_{p=0}^{n-1} a_p)^2} \\
= \frac{1}{n(\sum_{p=0}^{n-1} a_p)^2} + 2 \frac{n-1}{n(\sum_{p=0}^{n-1} a_p)^2} = \frac{1}{n(\sum_{p=0}^{n-1} a_p)^2}
\]
\[ G_{NL} = \sqrt{\left(\sum_{i=0}^{n-1} a_i^2\right)\left(\sum_{i=0}^{n-1} b_i^2\right)} > 1 \] (5.37)

**Proposition 6:** The noise level for the interleaved measurement topology is always larger than that of the conventional topology.

**Noise level gains for two nonzero entries**

The first row of the general measurement matrix with two nonzero row entries is \([1, q, 0, \cdots, 0]\). The square of noise level gain can be expressed as

\[ G_{NL}^2 = \left(\sum_{i=0}^{n-1} a_i^2\right)\left(\sum_{i=0}^{n-1} b_i^2\right) = \frac{\alpha}{n} \sum_{p=0}^{n-1} \frac{(1 + q)^2}{(1 + qe^{j\theta_p})(1 + qe^{-j\theta_p})} \] (5.38)

where \(\theta_p = 2p\pi/n\).

The derivative of the term is

\[ \frac{dG_{NL}^2}{dq} = \frac{\alpha}{n} \sum_{p=0}^{n-1} \frac{(e^{j\theta_p} + e^{-j\theta_p} - 2)(q^2 - 1)}{(qe^{j\theta_p} + 1)^2(qe^{-j\theta_p} + 1)^2} \] (5.39)

The two terms in the denominator are conjugate pairs, so their product is always positive. The first term in the numerator is always smaller than zero because the sum of the conjugate pairs are smaller than 2. Given the fact that \(q\) and \(G_{NL}\) are always positive, the following relation holds for the case of two nonzero entries

\[ \frac{dG_{NL}}{dq} \begin{cases} > 0 & q \in (0, 1) \\ = 0 & q = 1 \\ < 0 & q \in (1, +\infty) \end{cases} \] (5.40)

Equation (5.40) indicates that the global maximum of \(G_{NL}\) is at \(q = 1\). The above analysis proves that, given two nonzero entries, the measurement noise level is the largest when \(q = 1\), and the measurement noise level can be decreased by varying the value of \(q\).

### 5.3.7 Simulation

Simulations are set up in MATLAB to demonstrate the trend of the noise level gain. In the simulation, the measurement noise is white, and its standard deviation
is linear with the range of the voltage sensors. The cell voltage values are then calculated from the contaminated measurements and the standard deviation of the calculated cell voltages is compared with that of the conventional sensor topology. The cell voltages are set to be 3 V, $n$ ranges from 3 to 12, and $q$ ranges from 0 to 5 at a step of 0.01. The noise level gains are plotted in Figure 5.16.

![Figure 5.16: Simulated $G_{NL}$ for different $q$ and different $n$.](image)

Here list several important observations from Figure 5.16:

i) The $G_{NL}$ converges to 1 as $q$ goes to 0. This is because when $q$ equals to 0, the measurement topology is equivalent to the conventional sensor topology.

ii) The $G_{NL}$ converges to 1 as $q$ goes to infinity. An extension from Proposition 4 shows that the $G_{NL}$ does not change when all the row entries are multiplied by a nonzero number. Denote the measurement matrix with first row entries of $[1, q, 0, \cdots, 0]$ as $\text{circ}(1, q, 0, \cdots, 0)$. Then the $G_{NL}$ of $\text{circ}(1, q, 0, \cdots, 0)$ is the same as that of $\text{circ}(q^{-1}, 1, 0, \cdots, 0)$, which is obviously the same as $\text{circ}(1, q^{-1}, 0, \cdots, 0)$. As $q$ goes to infinity, the proposed topology converges to the conventional measurement topology and $G_{NL}$ converges to 1.
iii) The $G_{NL}$ is always greater than 1 except at $q = 0$. This matches the derivation in Proposition 6.

iv) When $n$ is an even number, the $G_{NL}$ goes to infinity at $q \to 1$, as illustrated by the dashed lines. When $q = 1$, $n$ and $k$ should be relative prime to obtain invertible $A$ matrices. However, the even numbers are not prime to $k$ in this case. Therefore, the measurement topology cannot be solved, and the $G_{NL}$ goes to infinity.

v) When $n$ is an odd number, the $G_{NL}$ is at its global maximum at $q = 1$, as illustrated by the solid lines. This matches the derivation in Section 5.2.

5.3.8 Experiment

In order to demonstrate the broader application of the improved measurement topology, an experiment is conducted for the case of $n = 6$ with two nonzero first row entries of 1 and 0.5. It needs to be noticed that $n = 6$ is not invertible in the previous work where both of the two row entries are 1. The schematic of the experimental setup is shown in Figure 5.17, and the picture for the interleaved measurement circuit board is given in Figure 5.18.

![Figure 5.17: Schematic of experiment setup.](image)
The UDDS is applied to the six-cell string, and an ESC fault is induced at 200.7 s by shorting $C_3$. The results of the cell fault experiment are given in Figure 5.19. The sensor fault is induced at 173.4 s by disconnecting the jump wire in the sensing trace of $V_6$. The results for the sensor fault experiment are given in Figure 5.20.

As introduced in Sec. 5.2.2, the fault can be distinguished and isolated by the specific patterns indicated by the cell fault or sensor fault signals. Figure 5.19c and Figure 5.19d show that $C_3$ is in fault condition, because 1) it is almost impossible for both $V_2$ and $V_3$ to be in fault condition at the same time; 2) the fault signals in Figure 5.19d follow the specific pattern of $[0, 0.5, 1, 0, 0, 0]^T$, which is the third column of $\text{circ}(1, 0.5, 0, 0, 0, 0)$, indicating abnormal changes on $C_3$.

Likewise, Figure 5.20a and Figure 5.20b demonstrate the sensor fault on $V_6$ because the cell fault signals follow the last column of the inverse of $\text{circ}(1, 0.5, 0, 0, 0, 0)$. Thus, the sensor fault on $V_6$ can be determined.
(a) Sensor readings ($V$).

(b) Calculated cell voltages ($C$).

(c) Sensor fault signals ($V_{\text{fault}}$).

(d) Cell fault signals ($C_{\text{fault}}$).

**Figure 5.19:** Experiment results for cell fault diagnostic at 200.7 s.
Figure 5.20: Experiment results for sensor fault diagnostic at 173.4 s.
5.4 Extension to sequential measurement

5.4.1 Impact of sequential measurement

The sequential update for the prevailing sensor topology uses zero order hold between samples. An example of $n = 3$ and $k = 2$ is used to demonstrate its principle. If the sequential update is applied to the proposed method, the update formula for $C_1$ can be expressed as

\[
\begin{align*}
C_1[m] &= e_{1,1}V_1[m-2] + e_{1,2}V_2[m-1] + e_{1,3}V_3[m] \\
C_1[m+1] &= e_{1,1}V_1[m+1] + e_{1,2}V_2[m-1] + e_{1,3}V_3[m] \\
C_1[m+2] &= e_{1,1}V_1[m+1] + e_{1,2}V_2[m+2] + e_{1,3}V_3[m] \\
C_1[m+3] &= e_{1,1}V_1[m+1] + e_{1,2}V_2[m+2] + e_{1,3}V_3[m+3]
\end{align*}
\]

(5.41)

where $C_1[m]$ is the voltage value of $C_1$ at time $m$, $V_i[m]$ is the updated voltage measurement of sensor $i$ at time $m$, and $e_{1,1} = 0.5$, $e_{1,2} = -0.5$ and $e_{1,3} = 0.5$ for $n = 3$ and $k = 2$. In this sequential update algorithm, one $V_i$ is updated after every sampling interval, as a result of which, $C_1$ is updated after every sampling interval.

A simulation is run based on the update algorithm, where the following assumptions are made,

i) The three batteries are consistent.

ii) The terminal voltages of all the batteries jump from 3.0 V to 3.1 V at time $m + 1$.

Base on the simulation, a voltage ripple is observed after the step input, as shown in Figure 5.21. This voltage ripple can be explained when (5.41) is rewritten as (5.42).

\[
\begin{align*}
C_1[m+1] - C_1[m] &= e_{1,1}\{V_1[m+1] + V_1[m-2]\} \\
C_1[m+2] - C_1[m+1] &= e_{1,2}\{V_2[m+2] + V_2[m-1]\} \\
C_1[m+3] - C_1[m+2] &= e_{1,3}\{V_3[m+3] + V_3[m]\}
\end{align*}
\]

(5.42)

As can be calculated from (5.42), from time step $m$ to $m + 1$, $C_1$ is increased by 0.1 V, from $m + 1$ to $m + 2$, $C_1$ is decreased by 0.1 V, and from $m + 2$ to $m + 3$, $C_1$ is increased by 0.1 V. The ripple in Figure 5.21 results from the latter two changes.
Indeed, the effect of the ripple can be larger given larger $n$ and $k$, as shown in Figure 5.21, where the case of $n = 5$ and $k = 3$ is also demonstrated.

**Figure 5.21:** Voltage ripples are found in sequential measurement.

**Figure 5.22:** The general sequential update process.

The simulation result shows that it takes a whole sampling cycle to update every sensor measurement, and the voltage ripples appear during the update process.
The general update process is illustrated in Figure 5.22 qualitatively. Since the final terminal voltage settles at the right value, all the voltage ripples add up to the voltage step increase, i.e,

\[ C_i[m + n] = C_i[m] + \sum_{j=1}^{n} e_{i,ind(p+j,n)} \{ V_{ind(p+j,n)}[m + j] - V_{ind(p+j,n)}[m + j - n] \} \tag{5.43} \]

where \( ind(p + j, n) \) is the rotating sensor index,

\[ ind(x, n) = \begin{cases} \ n & \text{rem}(x, n) = 0 \\ \ rem(x, n) & \text{otherwise} \end{cases} \tag{5.44} \]

where \( \text{rem}(x, n) \) is the remainder of \( x/n \).

Equation (5.43) shows that sensor \( p + 1 \) senses the voltage step increase first and each succeeding voltage sensors is updated one per time step, until sensor \( p \) is updated and the cell voltage converges to the right value. The whole process takes \( n \) time steps, which equal one full sampling cycle.

It can be found that these voltage ripples increase measurement noise significantly. As expected from Figure 5.22, the noise is proportional to the \((k - 1)/k\) times voltage change in sensors and thus increases linearly with \( k - 1 \). Given 100 mV instant terminal voltage change for one cell in dynamic operation, the sequential measurement will lead to 100 mV measurement error for \( n = 5 \) and \( k = 3 \), which is not desirable.

The other impact of the sequential measurement is on fault detection and isolation. Since all the voltage sensors are updated sequentially, the fault signals becomes a time series of signals. For example, as the case of Figure 5.21, the sensor voltages will not all change at 300 s. Due to sequential sensor updates, the change of \( V_3 \) will lag that of \( V_2 \) for one time step. With this impact, the fault detection and isolation need to be adapted from examining signal changes at one time to examining signal changes within a sampling period. In addition, as discussed in Sec. 5.2.2, the voltage change in one sensor reading is regarded as sensor fault, which is always the case in sequential measurements. Therefore the extension of the proposed method to sequential measurement requires much more work in signal processing, more memory space and more computation.
5.4.2 Conversion of sequential measurement to simultaneous measurement

Given the limitation in the extension of the proposed topology to sequential measurement, a conversion methodology is provided to modify sequential measurement to simultaneous measurement in practical application.

Assume a battery module consists of $M$ cells in series, and $N$ modules form a whole pack. Within one module, a set of sequential measurement circuit is used to measure the voltages. Thus, a total $N$ ADC channels and $N$ measurement circuits are utilized.

In the traditional arrangement, the cell voltage is updated sequentially within one module, which leads to undesired sequential update.

The traditional arrangement can be modified by the following procedure,

i) The $NM$ cells in the pack are regrouped into $M$ new modules with $N$ cells in each module.

ii) For one time step, all the $N$ ADC channels are used to measure the cell voltages within one module, and the cell voltages in other modules are updated sequentially.

In this way, the sequential cell voltage measurement in traditional topology is adapted to its equivalent simultaneous cell voltage measurement topology, with module voltage sequentially updated.

5.5 Optimal selection of row entries

The simulation and experiment demonstrate that the row entries of the measurement matrix have substantial effect on the performance of the corresponding measurement topology. The effects are discussed in detail as follows, and they are summarized in Table 5.1.

First, from the cost perspective, $k$ should be as small as possible ($k \leq 2 < n$), because the number of switches increases as $k$ increases.
Table 5.1: Limitation and preferred choice of the first row entries of the measurement matrix.

<table>
<thead>
<tr>
<th>Limitation</th>
<th>Preferred choice</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost</td>
<td>Small $k$, consecutive and all ‘1’s.</td>
</tr>
<tr>
<td>Invertibility of topology</td>
<td>Geometric series.</td>
</tr>
<tr>
<td>Noise</td>
<td>Noise can be reduced by varying $q$ (max. at $q = 1$).</td>
</tr>
<tr>
<td>Diagnosis confidence</td>
<td>Negligible improvement when $k \geq 2$.</td>
</tr>
</tbody>
</table>

Second, from the invertibility perspective, the interleaved topology can be more widely applied by varying the row entries. One universal solution is the row entries in geometric series as (5.19). Combined with the first point, the best candidate for the first row entries is 1 and $q$ followed by all zeros ($q \neq 1$).

After that, from the noise perspective, the maximum noise level occurs when $q = 1$ for two nonzero row entries. The lower bound of the noise level gain cannot be achieved, however, an appropriate value of $q$ can be selected such that the noise level is reduced.

Next, it needs to keep in mind that $q$ should not be too small for the voltage measurements to be identified from other source of noises, and $q$ should not be too large due to its corresponding increase in the voltage level of the power supplies for the measurement circuits.

In addition, the previous work shows that the confidence level of the fault distinction increases as $k$ increases. However, it also shows that the confidence level has negligible improvement when $k$ is larger than 2.

In summary, the optimal choice of $k$ is 2 and the two nonzero entries are 1 and $q$, where $q \neq 1$.

5.6 Relation to coding theory

The $A$ matrices discussed in the above sections are similar to the generator matrices in coding theory, more specifically, those in Hamming codes. It is worthwhile discussing the similarities and differences of Hamming codes and the interleaved
voltage measurement method. Hamming codes are applied to detect error bits transmitted in telecommunication by adding parity bits. Based on the introduction in [82], the following relation holds in Hamming codes

\[ E(x) = xG \]  \hspace{1cm} (5.45)

where \( x \) is a 1×\( k \) matrix containing the message to be transmitted, the \( k \times n \) generator matrix \( G \) encodes the message, and the 1×\( n \) matrix \( E(x) \) is the encoded message. A typical \( G \) matrix for a 3-bit message is given in

\[
G = \begin{bmatrix}
1 & 0 & 0 & 1 \\
0 & 1 & 0 & 1 \\
0 & 0 & 1 & 1 \\
\end{bmatrix} \hspace{1cm} (5.46)
\]

where the parity bit is the sum of the 3-bit message. This parity bit can be used to detect error in data transmission.

It is interesting to note that the structure of (5.45) is similar to that of (5.1), except a transpose operation on both sides. The \( C \) can be regarded as the message to be transmitted, \( A \) is the generator matrix, and \( V \) is the encoded data. Furthermore, if the measurement topology in Fig. 5.1c is written in the matrix form, the resultant \( A \) matrix is similar to the \( G \) matrix in (5.46), as

\[
A = \begin{bmatrix}
1 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 \\
1 & 1 & 1 & 1 & 1 \\
\end{bmatrix} \hspace{1cm} (5.47)
\]

However, there are still several differences between the interleaved voltage measurement method and Hamming codes that need to be clarified,

i) The parity bit in Hamming codes is similar to the redundancy in the battery application, which is tried to be avoided in this thesis.

ii) Hamming codes do not consider the situation, in which the measurement channel goes wrong permanently in the transmission process.
iii) In battery application, given a same current in a series string, the voltage of cells are expected to follow a same increase/decrease trend. This is the key to distinguish sensor/cell failure, but this is not applicable in Hamming codes, in which the message variation patterns cannot be determined.

5.7 Summary

A fault-tolerant voltage measurement method is proposed for the BMS of EVs with no extra sensor or software added. A matrix interpretation is developed to represent sensor topologies. The analysis shows the viability of the proposed measurement topology in isolating cell failure and sensor failure by measuring the voltage sum of multiple battery cells. Through the use of this concept, the confidence of sensor failure and cell failure detection are greatly improved, while no additional cost is added to the system. Simulation and experiment results show that sensor and cell faults can be identified and isolated by locating the abnormal signals. The robustness of the method is tested by applying UDDS cycles to the cells and no false detection is induced by normal operation behavior.

Next, the voltage measurement method is generalized to n series connected cells with $k$ consecutive voltage sum measurement. Reliability prediction analysis shows the increase of $k$ will improve the fault detection confidence level. The application of probability theory indicates that the increase of $n$ and $k$ will increase noises levels in the calculated cell voltage values, whereas the decrease of $n$ will limit the upper bound of $k$. Simulation shows that the application of the proposed method is limited in sequential measurements, however, with a proposed procedure, a sequential measurement topology can be always converted into an equivalent simultaneous measurement topology. The feature of valid measurement topology, i.e. the condition of $n$ and $k$ to construct invertible $A$ matrix, is discovered by mathematical proof as that $n$ and $k$ need to be relatively prime to each other.

Later, the improved interleaved sensor fault isolation and detection methodology is introduced, and a new proof to the coprime relation is provided. A graphical interpretation is developed to visualize the impact of $n$ and $k$ choices to the invertibility of the measurement matrix. An improved measurement matrix is then proposed.
based on the graphical interpretation, which removes the coprime constraint by assigning different row entries. A comprehensive noise analysis is conducted and reveals that the improved method has lower noise levels than the basic interleaved measurement method.

The advantages and disadvantages of the proposed method is summarized in Table 5.2. This method fully utilizes duplicated components in the sensing circuit, and interleaves them to increase fault detection credibility. The major limitation of this method are 1) the range of the sensors are increased, then the cost will increase, and 2) the noise is increased. It needs to be noted that this fault-tolerant measurement concept can also be further extended to other physical quantity measurements in which distinction between sensor faults and device faults is critical.

Table 5.2: Advantages and disadvantages of the proposed sensing topology.

<table>
<thead>
<tr>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fully utilize duplicated components.</td>
<td>Lead to higher noise level.</td>
</tr>
<tr>
<td>Require no additional components.</td>
<td>Require higher sensor range.</td>
</tr>
<tr>
<td>Distinguish between sensor/cell failure.</td>
<td></td>
</tr>
</tbody>
</table>

This chapter is based on the following published papers,


Chapter 6

The integrated self-redundant fault detection method

6.1 Introduction

In the previous two chapters, the concept of self-redundant fault detection is introduced, analyzed and validated. This idea is first applied in cell failure detection (Chapter 4). A cell failure can be marked when it has off-trend responses, which saves the effort in battery cell modeling. Then, this idea is utilized in sensor failure detection in the battery systems (Chapter 5). The correlation of cell voltage values and the sensor readings are optimized, such that the voltage of each cell is associated with multiple voltage sensors, enabling the cell/sensor failure distinction.

For the ease of analyzation, the two applications of the concept are separately presented. Indeed, the two methods are not exclusive to each other, and can be integrated to achieve the merits of both.

This section demonstrates the viability of the integrated self-redundant fault detection method. The experiment results from Chapter 5 is revisited, and the fault determination is improved by utilizing the correlation-based fault detection method.
6.2 Integration of the two methods

The symbol notation in (5.1) is extended to this section, where the \( n \) series connected cell voltages are represented as the column matrix \( C \), the \( n \) voltage sensor readings are represented as the column matrix \( V \), and they are correlated by the \( n \times n \) matrix \( A \).

Then the cell voltages can be calculated by the sensor voltage readings and the specific sensor topology, which is characterized by \( A \). After that, the correlation coefficient of the cell voltages obtained can be calculated by (4.4) recursively. The general procedure of the integration is illustrated by Figure 6.1.

![Figure 6.1: Execution diagram of the integrated self-redundant fault diagnosis.](image)

6.3 Results and discussion

6.3.1 Cell fault

The experiment data in Chapter 5 is revisited with the same topology as Figure 5.2. It needs to be noted that the experiment data are modified such that the variation in the either the sensor readings or the calculated cell voltages cannot be simply identified by the threshold method. For example, the calculated cell voltages based on the inverse sensor matrix are given in Figure 6.2. The obvious cell voltage drop in Figure 5.8b is reduced as that in Figure 6.2, making it hard to distinguish by the simple threshold-based method.

The corresponding correlation coefficients are calculated for the neighboring
cells, as given in Figure 6.3. In the calculation, the amplitude of the added square wave is increased to 10 mV due to the noise level increase in the interleaved method. The period of the square wave is 2 samples. The window size for the correlation
coefficient calculation is 30 samples.

![Graph showing sensor measurements over time](image)

**Figure 6.4:** Direct sensor measurement for methods integration (cell failure).

![Graph showing correlation coefficients](image)

**Figure 6.5:** Correlation coefficients of voltage measurements (cell failure).

It can be seen that $r_{(1,2)}$ and $r_{(2,3)}$ both drop at the same time. Given the
assumption that only one fault takes place at a time instant, a conclusion can be drawn that cell #2 has an off-trend voltage behavior, and thus a fault occurs on this specific cell.

The direct sensor measurements are given in Figure 6.4, and the correlation coefficients of the sensor measurements are provided in Figure 6.5. The abnormal drops in the correlation coefficients are observed in \( r_{(2,3)} \) and \( r_{(5,1)} \), indicating abnormal voltage readings in both \( V_1 \) and \( V_2 \). This matches with the analysis in Sec 5.2.4.

6.3.2 Sensor fault

The sensor fault data in Sec 5.2.4 are modified and discussed in this section. The direct sensor measurements are presented in Figure 6.6, and the corresponding correlation coefficients are given in Figure 6.7. A same square wave is added as that in Sec. 6.3.1. The sudden drops in \( r_{(3,4)} \) and \( r_{(4,5)} \) indicate that abnormal variation is found on \( V_4 \).

![Figure 6.6: Direct sensor measurement for methods integration (sensor failure).](image)

The calculated cell voltages based on the data in Figure 6.6 are demonstrated in Figure 6.8, and the correlation coefficients of the cell voltages are given in Figure
Figure 6.7: Correlation coefficients of voltage measurements (sensor failure).

6.9. The sensor failure on $V_4$ leads abnormal cell voltage variations, which is not practical in real applications. As a result, the sensor failure can be determined because one sensor failure has higher probability to occur than multiple cell failures at a same time. This failure cannot be directly distinguished by the threshold-based method since the voltage variations are within the safe operation range.

6.4 Summary

In this section, the feasibility of combining the interleaved voltage measurement method and the correlation-based fault detection method is demonstrated. The experiment data in Sec. 5.2.4 are modified such that the fault on the sensor and cell cannot be easily captured by the threshold-based method. Then, the correlation-based method introduced in Chapter 4 is applied to capture and isolate the faults. By analyzing the calculated correlation coefficients of the modified experiment data, it is verified that the off-trend voltage behaviors at fault conditions are successfully identified. In summary, the integrated method demonstrates the merits that 1) the sensor/cell failure is achieved and 2) the correlation coefficient can better detect the
off-trend failure than the traditional threshold-based method.

**Figure 6.8:** Calculated cell voltages in methods integration (sensor failure).

**Figure 6.9:** Correlation coefficients of calculated cell voltages (sensor failure).
Chapter 7

Conclusion and future work

7.1 Conclusion

This thesis introduces the self-redundant fault diagnosis of battery systems in the electrified vehicles, as opposed to the traditional redundancy-based fault diagnosis methods, in which either a duplicative system or a mathematical model is utilized to provide an output/state to compare with that of the true system.

The threshold-based fault detection is first studied. Abundant experiments are conducted to emulate the voltage, current and temperature responses of the failure battery cells, and an integrated electric fault detection algorithm is constructed. The results show that the over charge and over discharge faults can be easily captured by the voltage threshold values because of the nature of the fault, whereas the method may have false negative detections for the ESC and ISC faults.

Then the model-based fault diagnosis is applied to compensate for the ignorance of input information in the threshold-based methods. The continuous-time system identification method is applied to estimate the parameters of the ECM and the models are proved to be more accurate and robust than the traditional DT system identification methods. The model-based method manages to capture the short circuit fault when the voltage does not exceed the operation limit. However, this method requires preliminary efforts in battery modeling, identification and validation, and is not robust to cell inconsistencies. Except that, the detected faults may come from an inaccurate model.
To address the drawbacks of the redundancy-based method, the correlation-based fault diagnosis method is proposed to detect the short circuit faults. This method compares the output of the multiple battery cells within a battery pack, and flags a fault when any of the cell is off the trend of voltage variations in real applications. Therefore, any cell in the battery pack can serve as a redundancy for all the other battery cells, even though there is not a physical redundancy. An essential merit of the method is that it does not require any work in battery testing, modeling and validation. Due to the properties of the correlation coefficient, the method is also robust to cell inconsistencies in SoC and SoH. It needs to be noted that the threshold-based voltage detection should be combined with this method in case the whole pack experiences short circuit at the same time.

After that, this work presents the interleaved voltage measurement method to distinguish between sensor and cell failure without additional components. This method resolve the ambiguity when an abnormal reading is obtained from the voltage sensor: if the sensor reading is trusted, a cell fault is determined, while if the cell condition is trusted, a sensor fault is indicated. After that, the interleaved voltage measurement method is improved such that its applicability is enhanced and the noise level is formulated mathematically.

Finally, the interleaved voltage measurement method is integrated with the correlation-based fault detection method, and the merits of both methods are achieved. The viability of the integrated method is demonstrated.

The major contribution of this thesis is the development of the self-redundant fault diagnosis methods. These methods utilize the duplicative components in the battery systems. The duplicative voltage sensors are interleaved to increase the credibility of voltage measurement, and the duplicative cells in the pack are compared with each other to indicate fault when any of the cell is off the general voltage variation trend. The self-redundant fault detection method does not require hardware and analytical redundancies, and increases the confidence levels of the fault detections.
7.2 Future work

i) It is discussed in Chapter 2 that the threshold-based fault diagnosis method is the dominating fault diagnosis approach in the real battery systems, due to its ease of implementation, low computation cost and robust performance. One of the major future work is to implement the self-redundant fault detection method online in real vehicles. Even though the working principles have been analyzed, the robustness still needs to be verified by real applications.

ii) The correlation coefficient-based method has a fixed time window. It still requires continuing effort in determining a proper window size to identify the short circuit fault, especially when the short resistance is large.

iii) It needs to be noted that the correlation coefficient-based method can be combined with analytical redundancy to further improve the credibility when fault occurs, and save the pack level voltage monitoring.

iv) As the development of the intelligent systems, people are more and more familiar with the concept of connected vehicles. The self-redundant fault detection method are not limited to a local battery pack. When all the vehicle data are available on the cloud, the responses of the vehicles can be compared with each other. In other words, all the other similar vehicles can be the hardware redundancy of your vehicles. If the vehicle responses are different from the real-time data or historical data of other similar vehicles in a similar situation, chances are that the target vehicle is in a fault condition.
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